Integrated active noise control and sound quality enhancement system for hearing devices

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**NANYANG
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SINGAPORE

**INTEGRATED ACTIVE NOISE CONTROL AND SOUND
QUALITY ENHANCEMENT SYSTEM FOR HEARING
DEVICES**

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SCHOOL OF ELECTRICAL & ELECTRONIC ENGINEERING

2020

INTEGRATED ACTIVE NOISE CONTROL AND SOUND QUALITY ENHANCEMENT SYSTEM FOR HEARING DEVICES

VALIANTSIN BELYI

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Authorship Attribution Statement

This thesis contains material from 2 papers published in the following peer-reviewed tier 1 journals and 2 papers published in the following conference proceedings where I was the first author.

Chapter 3 is published as V. Belyi and W. S. Gan, “Psychoacoustic subband active noise control algorithm,” in *Proceedings - 9th Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2017*, 2018, vol. 2018-Feb, pp. 457–463. DOI: 10.1109/APSIPA.2017.8282075.

The contributions of the co-authors are as follows:

- Prof. Woon-Seng Gan provided the initial project direction, supervised this research topic and edited the manuscript drafts.

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- Prof. Woon-Seng Gan provided the initial project direction, supervised this research topic and edited the manuscript drafts.

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Table of Contents

Statement of Originality	II
Supervisor Declaration Statement.....	III
Authorship Attribution Statement.....	IV
Acknowledgments	VI
Table of Contents	VIII
Summary	1
List of Figures.....	4
List of Tables	9
List of Acronyms.....	11
List of Notation	13
Chapter 1.....	15
Introduction.....	15
1.1 Motivation	15
1.2 Objectives.....	18
1.3 Major Contributions of the Thesis.....	19
1.4 Organization of the Thesis	22
Chapter 2.....	23
Literature Review on ANC and Psychoacoustic Algorithms	23
2.1 Description of ANC Algorithm.....	23
2.1.1 ANC Algorithm Working Principles	23
2.1.2 Feedforward ANC Algorithm	25
2.1.3 Integrated Audio ANC Algorithm.....	29
2.1.4 Overview of Noise Cancellation Headphones.....	31
2.2 Psychoacoustic Analysis and Masking	34
2.2.1 Human's Hearing System	34
2.2.2 Principles of Psychoacoustic Masking	37
2.2.3 Frequency Masking Approach	39
2.2.4 ANC Algorithm and Masking Integration	42
2.3 Binaural Algorithms	44
2.3.1 Binaural Hearing	44
2.3.2 Binaural Noise Reduction Techniques.....	47

2.4	Conclusions.....	50
Chapter 3.....		51
Psychoacoustic Subband ANC Algorithm.....		51
3.1	Subband ANC Algorithms.....	51
3.1.1	Subband Adaptive Filter.....	51
3.1.2	Subband ANC Algorithm.....	55
3.2	Description of the Psychoacoustic Subband ANC Algorithm.....	57
3.2.1	Critical Bands Filter Bank.....	57
3.2.2	Non-uniform Critical Bands Subband Adaptive Filter	61
3.2.3	Psychoacoustic ANC Algorithm	64
3.3	Analysis of Psychoacoustic Subband ANC Algorithm Performance..	70
3.3.1	Systems for Comparison.....	70
3.3.2	Simulation Results	71
3.4	Conclusions.....	76
Chapter 4.....		77
Integrated Psychoacoustic Subband ANC and Masking System		77
4.1	ANC and Masking Integration.....	77
4.1.1	Psychoacoustic Model for Integrated System	78
4.1.2	Automatic Gain Control (AGC) algorithm.....	84
4.1.3	Musical Genres and Noise Types Patterns.....	90
4.2	Analysis of Psychoacoustic Subband ANC and Masking System	95
4.2.1	Approaches for Comparison	95
4.2.2	Objective Evaluations	97
4.2.3	Subjective Evaluations.....	101
4.2.4	Advantages and Disadvantages of Compared Approaches.....	104
4.3	Conclusions.....	106
Chapter 5.....		107
Binaural and Combined Bilateral/Binaural ANC Algorithms for Headphones		107
5.1	Binaural ANC Algorithm	108
5.1.1	Binaural FxNLMS Algorithm.....	109
5.1.2	Theoretical Considerations of Binaural ANC Algorithm	114
5.1.3	Single Noise Source Scenarios	117
5.1.4	Multiple Noise Sources Scenarios	129
5.1.5	Summarized Comparisons of Binaural and Bilateral ANC Approaches.....	135

5.2 Combined ANC Algorithm with Bilateral and Binaural Options for Headphones.....	136
5.2.1 Possible Environmental Noise Scenarios	137
5.2.2 Coherence-based Selection between Binaural and Bilateral ANC algorithms	137
5.3 Analysis and Results	141
5.3.1 Approaches for Comparison	142
5.3.2 Simulations/Real-time Experiments and Analysis of Results	143
5.3.3 Comparisons with Commercial ANC Headphones	149
5.4 Conclusions.....	158
Chapter 6.....	160
Binaural ANC Algorithm for Hearing Aids	160
6.1 Introduction in Hearing Aids and Hearing Aids Environmental Noise Problems.....	160
6.1.1 Types of Hearing Aids.....	161
6.1.2 Environmental Noise Problems and HAs Noise Reduction Approaches.....	163
6.2 Binaural ANC Algorithm for Hearing Aids	164
6.2.1 ITE Hearing Aids Configurations.....	164
6.2.2 Considerations of Binaural ANC Algorithm for Hearing Aids Applications.....	167
6.3 Results and Discussions of Binaural ANC Algorithm for Hearing Aids	168
6.3.1 Single Noise Source Scenarios	168
6.3.2 Multiple Noise Sources Scenarios	170
6.4 Occlusion Canceller for Hearing Aids.....	172
6.4.1 Occlusion Effect.....	172
6.4.2 Adaptive Algorithm for Occlusion Effect Cancellation	173
6.4.3 Results of the Adaptive Occlusion Effect Canceller	175
6.5 Conclusions.....	177
Chapter 7.....	179
Conclusions and Future Work	179
7.1 Conclusions.....	179
7.2 Future Works.....	182
References	185
Appendix A: Hardware Specifications.....	198

A.1 DSP Board TMS320C6713DSK Specification	198
A.2 KEMAR Dummy Head Specifications	199
A.3 Beyerdynamic – Custom One Plus Headphones Specifications.....	200
Appendix B: Real-time Experimental Arrangements.....	202
B.1 The Microphones Positions and Experimental Arrangement for Single-and Multiple-noise Sources Scenarios	202
B.2 The Diffused Field Experimental Setup.....	204
B.3 The Microphones Positions for The HAs Experiments.....	204

Summary

Headphones are essential devices of modern life. People use them to listen to music on the go, to communicate with each other and to reduce the surrounding noise disturbances. With the increase of the headphones market, requirements for headphones also become more specific. The sound quality of the playback system is one of the most important characteristics of headphones. Moreover, high-level environmental noise prevents full usage of headphones and makes the target sound (music or speech) unpleasant and hardly audible. Therefore, active noise cancellation becomes an important function of modern headphones. However, commercial noise-cancellation headphones do not always pay enough attention to the quality of the music. Another issue is poor noise reduction performance for real-life multiple environmental noise cases. Moreover, noise reduction bandwidth is limited. With the aim to solve these issues and to improve users' experience, this thesis focuses on the development and implementation of the system, which is able to enhance noise reduction performance and sound quality for headphones applications at the same time.

Three areas are combined to get a wider view of the current issues and to find solutions in the integration and development of combined approaches from different algorithms. An active noise control (ANC) algorithm is the first area. Commercial noise-cancellation headphones widely use conventional fixed-filter ANC approach. However, direct ANC application does not provide analysis of the noise situation and cannot guarantee high-quality sound in the aggressive noise environment. These observations lead to the second research area, which is based on the psychoacoustic analysis. The psychoacoustic analysis helps to investigate and understand a human's hearing system. Psychoacoustic analysis and masking are used to analyze noise sources and relations between noise and music. Moreover, psychoacoustic algorithms have a strong connection with the human's hearing, which helps to improve the perceptual quality of sounds. The third research area is on the development of binaural algorithms to provide more natural processing and sound perception. It is well-known that the

human's hearing is binaural. Compare to monaural (bilateral) approaches, binaural algorithms have advantages in the localization and separation of sound sources. Therefore, it is useful for real-life multiple noise source cases.

This thesis begins with the fundamental analysis of the previous studies on all three research areas to investigate and discuss already existing techniques and combinations for headphones applications. The previous studies overview shows that ANC algorithms are commonly used in headphones without any further extension. Psychoacoustic masking is mostly used for perceptual equalizers. Binaural techniques are applied to extend simple noise reduction algorithms for hearing aids. However, there is no study that combines all these three significant research areas to get a high-efficient noise reduction system for headphones with the ability to improve the perceptual quality of sound. With the aim to fill this gap, a new integrated noise reduction and sound enhancement system is proposed in this thesis.

This thesis can be divided into a few parts. Firstly, psychoacoustic analysis is added to the conventional ANC system. As a result, the psychoacoustic subband ANC algorithm is proposed and implemented. The idea is to define and reduce audible noise components, ignoring inaudible noise. Results show the high perceptual quality of audio with reduced computational resources.

Secondly, the reduction of computational resources allows additional sound processing enhancement without degradation of real-time performance. Therefore, the psychoacoustic model is also used to add a masking algorithm and to propose a new integrated psychoacoustic ANC algorithm and masking system to improve the noise reduction performance of the conventional ANC algorithm. This system is developed to improve noise reduction performance of residual after ANC noise and enhance the perceptual quality of the sound. Objective and subjective experiments show the advantage of the proposed integrated system.

The third area that is proposed and developed in this thesis is on the noise reduction improvement of the real-life environmental noise cases. Real-life noise scenarios consist of multiple noise sources from different directions. Commercial noise cancellation headphones have poor performance in an

aggressive noise environment because of the limited number of acoustic sensors and processing units. Therefore, the conventional ANC algorithm is modified based on the binaural technique to obtain more relevant and full information about noise situation. Real-time results and comparisons prove the advantage of the proposed binaural ANC algorithm for headphones in terms of noise reduction performance for multiple noise sources. Moreover, the proposed technique was also evaluated in hearing aids devices. Real-time experiments showed that the binaural ANC algorithm is also efficient for hearing aid for different environmental noise scenarios.

This thesis proposes a new integrated noise reduction and sound enhancement system for headphones and hearing aids, based on three of the most important areas. The proposed system combines a noise reduction approach with psychoacoustic and binaural algorithms, which are strongly connected with the human's hearing system. Such integration leads to advantages of the proposed headphones system in terms of noise reduction and perceptual quality of sound.

List of Figures

Figure 1.1 – Passive attenuation of the Beyerdynamic – Custom One Plus headphones.....	17
Figure 2.1 – Idea of the ANC algorithm [15]	24
Figure 2.2 – Feedforward ANC algorithm (dash line indicates acoustic domain)	25
Figure 2.3 – Adaptive feedforward ANC algorithm diagram (dash line indicates acoustic domain)	27
Figure 2.4 – Integrated audio feedforward ANC algorithm (dash line indicates acoustic domain)	30
Figure 2.5 – ANC headphones [33]	31
Figure 2.6 - Sony WH-1000XM3; Bose QuietComfort 35 II	32
Figure 2.7 – Bose QuietComfort 35 II noise reduction performance [34].....	33
Figure 2.8 – Sony WH-1000XM3 noise reduction performance [35]	33
Figure 2.9 – Human’s hearing system [38]	35
Figure 2.10 – Human’s cochlear [39].....	36
Figure 2.11 – Hearing thresholds [42]	37
Figure 2.12 – Principles of temporal masking [42].....	38
Figure 2.13 – Masking thresholds of narrowband maskers [42]	40
Figure 2.14 – Masking thresholds of 1 kHz center frequency masker with different SPL [42].....	40
Figure 2.15 – Tone-by-tone masking [42].....	41
Figure 2.16 – Masking threshold of multiple harmonics [42].....	41
Figure 2.17 – ANC algorithm and masking integration (dash line indicates acoustic domain)	43
Figure 2.18 – Scheme of binaural hearing; A1 – primary auditory cortex, IC – inferior colliculus, CL – cochlea, AN – auditory nerve, SO – superior olivary complex [8]	44
Figure 2.19 – Monaural masking situation (tonal sound is the desired and broadband noise is masker) [57]	46
Figure 2.20 – Dichotic condition (tonal sound is the desired and broadband noise is masker) [57]	46
Figure 2.21 – Diotic condition (tonal sound is the target and broadband noise is masker) [57]	46
Figure 2.22 – Dichotic condition (tonal sound is the desired and broadband noise is masker) [57]	47

Figure 2.23 – Binaural multichannel Wiener filter noise reduction algorithm [62]	48
Figure 3.1 – SAF open-loop structure	53
Figure 3.2 – SAF closed-loop structure	54
Figure 3.3 – Delayless closed-loop SAF	55
Figure 3.4 – Subband integrated audio ANC algorithm	56
Figure 3.5 – Uniform to non-uniform filter bank transformation	59
Figure 3.6 – a) Frequency wrapping transformation with real-value phase parameter; b) Frequency wrapping transformation with complex-value phase parameter;	60
Figure 3.7 – Critical bands filter bank (25 critical bands)	61
Figure 3.8 – a) Input signal (500 Hz tone corrupted by white noise); b) Desire signal (500 Hz tone); c) Output of critical bands SAF; d) Error signal;	66
Figure 3.9 – CB filter banks of 25 and 18 bands	67
Figure 3.10 – Psychoacoustic subband ANC algorithm (dash line indicates acoustic domain) [73]	68
Figure 3.11 – Masking threshold and noise SPL	69
Figure 3.12 – a) Frequency response of primary path; b) Frequency response of secondary path	71
Figure 4.1 – MPEG/Audio coder block diagram	79
Figure 4.2 – Integrated psychoacoustic subband ANC and masking system [91]	80
Figure 4.3 – Masking threshold and SPL of residual noise [91]	85
Figure 4.4 – Block diagram of the AGC	86
Figure 4.5 – An example of an averaging table	87
Figure 4.6 – Average masking threshold of different musical genres, soft rock, classical music, blues/Jazz, hard rock, pop music, club music, rap/hip-hop	92
Figure 4.7 – SPL of different noise types, broadband white noise (blue), engine noise (red) traffic noise (green) and MRT noise (black)	93
Figure 4.8 – Masking thresholds of different musical genres, soft rock (red line), classical music (green line), Blues/Jazz (magenta line), hard rock (black line), pop music (blue line), club music (light blue), Rap/Hip-Hop (yellow line) and average noise SPL	93
Figure 4.9 – SPL of different noise types, broadband white noise (blue), engine noise (red) traffic noise (green) and MRT noise (black) and average masking threshold of 7 musical genres	94
Figure 4.10 – Masking algorithm for perceptual equalizer	97
Figure 4.11 – Psychoacoustic subband ANC algorithm based on A-weighting filtering, $h(n)$ is the impulse response of A-weighting filter	97

Figure 5.1 – Multiple noise source experimental arrangement	111
Figure 5.2 – Block diagram of the proposed binaural integrated audio ANC algorithm [116].....	113
Figure 5.3 – Block diagram description of primary and secondary paths group delays.....	115
Figure 5.4 – Phase difference requirements to satisfy the causality issue for the ANC algorithm	116
Figure 5.5 – Error microphone positions; 1 – 3 positions embedded in ear cups of headphones and position 4 inside the ear.	119
Figure 5.6 – Impulse responses of secondary paths for 4 error microphone positions; Position #1 – blue, Position #2 – black, Position #3 – Red and Position #4 - green.....	120
Figure 5.7 – Frequency responses of secondary paths for 4 error microphone positions; Position #1 – blue, Position #2 – black, Position #3 – Red and Position #4 - green.....	120
Figure 5.8 – Block diagram of multi-reference ANC algorithm (right channel only)	123
Figure 5.9 –a) Signal flow block diagram of multi-reference ANC algorithm (left channel only); b) Signal flow block diagram of binaural ANC algorithm (left channel only)	128
Figure 5.10 – Bilateral ANC and binaural ANC algorithms performances for overlapping noises (90° BBN(300 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on.....	134
Figure 5.11 – Bilateral ANC and binaural ANC algorithms performances for non-overlapping noises (90° BBN (700 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on.....	135
Figure 5.12 - Coherences for non-overlapping noise sources noises (90° BBN (700 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents direct-channel coherence; (red) cross-channel coherence [116].....	139
Figure 5.13 – Real-time noise reduction of 3 ANC approaches for overlapping noise sources across 3 noise sources directions, where (blue) represents Bilateral ANC on; (red) represents Binaural ANC on; (black) represents CBBANC on [116]	145
Figure 5.14 – Real-time noise reduction of 3 ANC approaches for non-overlapping noise sources across 3 noise sources directions, where (blue) represents Bilateral ANC on; (red) represents Binaural ANC on; (black) represents CBBANC on [116].....	146
Figure 5.15 – Bilateral ANC, binaural ANC and CBBANC algorithms performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on	

.....	147
Figure 5.16 – Bilateral ANC, binaural ANC and CBBANC algorithms performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on [116]	147
Figure 5.17 – Bilateral ANC, binaural ANC, and CBBANC algorithms performances diffuse field noise, where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on [116].....	149
Figure 5.18 – Bilateral ANC, binaural ANC, CBBANC algorithms and commercial Bose and Sony headphones performances for non-overlapping noise sources	150
Figure 5.19 – Bilateral ANC, binaural ANC, CBBANC algorithms and commercial Bose and Sony headphones performances for overlapping noise sources.....	151
Figure 5.20 – Performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the left channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on	155
Figure 5.21 – Performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the right channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on	156
Figure 5.22 – Performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the left channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on	157
Figure 5.23 – Performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the right channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on	158
Figure 6.1 – a) Behind-the-ear hearing aids; b) In the ear hearing aids; c) Completely-in-the-canal hearing aids; d) Invisible-in-the-ear hearing aid [156]	

.....	162
Figure 6.2 – Spectrums of bilateral ANC off/on for BBN (1 st ITE HAs configuration).....	165
Figure 6.3 – Spectrums of bilateral ANC algorithm off/on for BBN (2 nd ITE HAs configuration).....	167
Figure 6.4 – Spectrums of binaural ANC off/on for BBN (the left channel; 2 nd ITE HAs configuration).....	170
Figure 6.5 – Multiple noises spectrums of binaural ANC on/off for the left channel; Multiple noises spectrums of bilateral ANC on/off for the left channel;	172
Figure 6.6 – Block diagram of the adaptive occlusion effect canceller based on the modified feedback ANC algorithm	174
Figure 6.7 – Block diagram of the integrated binaural ANC algorithm and adaptive occlusion effect canceller for HAs applications (for the right channel)	176
Figure 6.8 – Occlusion effect without adaptive occlusion effect canceller (blue line) and with adaptive occlusion effect canceller (red line).....	176
Figure B.1 – Reference and error microphone's positions (Position #1) [116]	202
Figure B.2 – Real-time experiments' arrangement in the anechoic chamber [116]	203
Figure B.3 – Position of the microphone to capture residual noise and evaluate commercial ANC headphones performance.....	203
Figure B.4 – Experimental arrangement for diffuse field noise source	204
Figure B.5 – ITE HAs configuration #1	204
Figure B.2 – ITE HAs configuration #2	205

List of Tables

Table 3.1 Critical bands.....	58
Table 3.2 Frequency index k	64
Table 3.3 Contribution of subband weights to fullband filter	65
Table 3.4 Simulation result of different critical bands number ANC algorithm	66
Table 3.5 Noise attenuation and psychoacoustic evaluations for white noise [73]	73
Table 3.6 Noise attenuation and psychoacoustic evaluations for engine noise [73]	74
Table 3.7 Noise attenuation and psychoacoustic evaluations for traffic noise [73]	75
Table 3.8 Computational time estimation [73]	75
Table 3.9 Amount of audible noise components.....	76
Table 4.1 Masking performance evaluation scale	88
Table 4.2 Averaging table orders comparison results for traffic noise	88
Table 4.3 Averaging table orders comparison results for broadband noise....	88
Table 4.4 Pre-setup ANC modes.....	94
Table 4.5 Objective psychoacoustic evaluations for 0 dB SNR	99
Table 4.6 Objective psychoacoustic evaluations for -5 dB SNR.....	99
Table 4.7 Objective psychoacoustic evaluations for -10 dB SNR.....	99
Table 4.8 Noise inaudibility scores system [91].....	102
Table 4.9 Pleasantness scores system [91]	102
Table 4.10 Subjective psychoacoustic evaluations for 0 dB SNR	102
Table 4.11 Subjective psychoacoustic evaluations for -5 dB SNR	102
Table 4.12 Subjective psychoacoustic evaluations for -10 dB SNR	103
Table 4.13 Advantages and disadvantage of noise reduction approaches [91]	105
Table 5.1 Possible variations of binaural ANC implementations	110
Table 5.2 Simulation noise reduction results of the proposed binaural ANC and bilateral ANC algorithms for single noise source	113
Table 5.3 Simulation noise reduction results of the proposed binaural ANC and bilateral ANC algorithms for multiple noise sources	113
Table 5.4 Real-time noise reduction results of binaural ANC and bilateral ANC algorithms for single broadband noise source from different directions.....	121

Table 5.5 Experimental setup of multi-reference ANC algorithm [128].....	123
Table 5.6 Simulations setup for bilateral, binaural and multi-reference ANC algorithms.....	124
Table 5.7 Simulations noise reduction results for bilateral, binaural and multi-reference ANC algorithms	124
Table 5.8 Noise sources directions for real-time multiple noise source experiments [116].....	130
Table 5.9 Real-time noise reduction results of bilateral and binaural ANC algorithms.....	130
Table 5.10 Noise reduction performances' differences between binaural and bilateral ANC algorithms.....	133
Table 5.11 Direct- and cross-channel coherence measurements, based on real-time experiments [116]	138
Table 5.12 Simulations results of bilateral, binaural and CBBANC algorithms [116]	144
Table 5.13 Real-time noise reduction results of CBBANC algorithms [116] .	145
Table 5.14 Noise reduction differences between CBBANC and bilateral/binaural ANC algorithms [116]	146
Table 5.15 Noise reduction results of bilateral, binaural and CBBANC algorithms for diffuse field noise [116].....	148
Table 5.16 Coherence measurements for diffuse field noise scenario [116]	149
Table 6.1 Bilateral ANC noise reduction results for the ITE HAs configuration #1	165
Table 6.2 Bilateral ANC noise reduction results for the ITE HAs configuration #2	166
Table 6.3 Real-time noise reduction result of bilateral and binaural ANC for HAs for single noise source at 0° direction.....	169
Table 6.4 Real-time noise reduction result of bilateral and binaural ANC for HAs for single noise source at 90° direction.....	170
Table 6.5 Real-time noise reduction result of bilateral and binaural ANC for HAs for multiple noise sources.....	172
Table A.1 C6713 Processor characteristics.....	199
Table A.2 KEMAR dummy head specification	200

List of Acronyms

ADC	Analog-to-digital converter
AGC	Automatic gain control
ANC	Active noise control
ATH	Absolute threshold of hearing
BBN	Bandlimited broadband noise
BMLD	Binaural masking level difference
BTE	Behind-the-ear
CB	Critical bands
CBBANC	Combined bilateral/binaural active noise control
CIC	Completely-in-the-canal
DAC	Digital-to-analog converter
DFT	Discrete Fourier transform
DOA	Direction-of-arrival
FFT	Fast Fourier transform
FIR	Finite-impulse response
FxLMS	Filtered-x least mean squares
FxNLMS	Filtered-x normalized least mean squares
HAs	Hearing aids
HRTFs	Head-related transfer functions
IFFT	Inverse fast Fourier transform
IIC	Invisible-in-the-canal
ILD	Interaural level difference
ITD	Interaural time difference
ITE	In-the-ear
LMS	Least mean squares
MSE	Mean square error
NR	Noise reduction
SAF	Subband adaptive filter
SFM	Spectral flatness measurement
SNR	Signal-to-noise ratio
SPL	Sound pressure level

VAD Voice activity detector

List of Notation

$*$	Convolution operator
$\ \ $	Euclidean norm
$a(n)$	Audio signal
$a'(n)$	Audio signal passed through estimate secondary path
AM	Arithmetic mean
BW	Bandwidth
$C(f)$	Coherence
C_{Cross}	Cross-channel coherence
C_{Dir}	Direct-channel coherence
D	Decimation factor
$d(n)$	Desire signal
$e(n)$	Error signal
$E\{ \}$	Expectation operator
$e'(n)$	Residual noise
f	Frequency in Hz
$f(n)$	Synthesis filter impulse response
f_s	Sampling rate
$\mathbf{g}(n)$	Gain coefficients vector
$G_{aa}(f)$	Auto-spectral density
$G_{ab}(f)$	Cross-spectral density
GM	Geometric mean
$h(n)$	Analysis filter impulse response
i	Masker critical band
j	Maskee critical band
k	Frequency index
l	FFT bin index
L	Left channel
L	Order of the analysis filter
M	Number of subbands
m	Subband index
N	Adaptive filter order

n	Time index
N_s	Subband filters order
$P(l)$	Power spectrum
$\mathbf{p}(n)$	Primary path impulse response
$P(z)$	Primary path z-transform
R	Right channel
$\mathbf{r}(n)$	Vector of recorded audio masker
$\hat{\mathbf{s}}(n)$	Estimated secondary path impulse response
$\mathbf{s}(n)$	Secondary path impulse response
$S(z)$	Secondary path z-transform
$S_{i,j}$	Spreading function
$T(v)$	Masking threshold
TI	Time-invariant term
TV	Time-variant term
w	Frequency in radians
$W(l)$	Adaptive filter tap in frequency domain
$\mathbf{w}(n)$	Adaptive filter impulse response
$W_{opt}(z)$	Optimal Wiener filter z-transform
$x(n)$	Reference signal
$x'(n)$	FxNLMS input signal
$x'^{Bin}(n)$	FxNLMS input signal for binaural ANC
$y(n)$	Noise control signal
$y'(n)$	Noise control signal passed through secondary path
α	Coefficient of tonality
λ	Selection parameter
μ	LMS step size
v	Critical band number
σ	Coherences ratio

Chapter 1

Introduction

This chapter introduces the major motivations and ideas of the presented research work. This chapter begins with the description of existing research problems and their significance for ANC headphones. Major research questions are stated as well. The objectives of this research are elaborated, which leads to the major contributions of this thesis. Finally, the thesis organization is presented at the end of this chapter.

1.1 Motivation

Noise pollution becomes one of the key problems in modern cities. It is not only annoying but also influences people's health. Previous medical studies [1] - [2] show that high-level noise can cause many illnesses and can be harmful to the human's hearing system. Moreover, unwanted noise signals can prevent or interrupt communication between people. Based on the application areas, the requirements for noise control methods are different. For example, big factories and plants require zones of global noise reduction to protect workers' hearing systems from engine and construction noises. On the other hand, there are so-called, "private" or local noise control solutions, which are useful for small areas. Headphones are the main electronic devices, which are used to implement local noise control solutions and create a comfort zone for a single person. Headphones are often used with mobile devices, such as mobile phones and audio players, outdoors. Moreover, most public places are quite noisy in big cities. Therefore, it is reasonable to link environmental noise problem to the wide usage of headphones. The simplest way is to apply soundproof materials for headphones' ear cups. This approach called passive noise attenuation [3], it was implemented for aircraft's headsets at the first and then was extended for

commercial headphones. However, passive noise attenuation is effective only for the high-frequency noise. For example, the passive attenuation of the Beyerdynamic – Custom One Plus headphones (used in this work) is shown in Figure 1.1.

Users try to solve environmental noise problem [4] by increasing the volume of their playback system to mask out the environmental noise. However, this solution can cause distortions of sound, and listening experience is still unpleasant and annoying. Moreover, loud sound can damage a human's hearing system [5]. Therefore, it is still a question on how to protect people from environmental noise using headphones, create a personal zone of silence and save the natural sound of the music.

To address this problem, commercial audio and electronic companies begin to equip their headphones with the Active Noise Control (ANC) [6] modules. The ANC algorithm is widely used for different applications to reduce annoying environmental noise in the specific control area. Commercial noise-cancellation headphones must satisfy several requirements:

1. High noise reduction performance of the environmental noise;

Noise-cancellation headphones require at least 10 dB noise reduction, which corresponds to half of the loudness perception.

2. Do not introduce any additional artifacts;

The active noise control algorithm produces an additional noise-cancellation signal. Therefore, it is still possible to perceive additional artifacts or fill some unpleasant pressure at the eardrum.

3. Do not distort the target sound;

Headphones' emitters are used to produce both music and noise-cancellation signals at the same time. So, the music sound can be corrupted and/or masked.

Modern noise-cancellation headphones mostly satisfy these requirements. However, there are ways to improve existing noise-cancellation headphones, especially in terms of noise reduction performance. The ANC algorithm is efficient only for low-frequency noise signals, below ~1500 Hz [7].

Figure 1.1 – Passive attenuation of the Beyerdynamic – Custom One Plus headphones

Moreover, noise reduction performance strictly depends on the headphones' emitter specifications. Noise-cancellation headphones tests show that noise reduction performance degrades with increasing noise sources number. This observation cannot be ignored because real-life environmental noise scenarios consist of multiple noise sources, situated in different directions. Therefore, ANC headphones can be further improved in terms of high-frequency (> 1500 Hz) noise reduction and multiple-noise sources reduction. Another way of improvement is based on the perceptual abilities and hearing features of humans. All existing noise-cancellation headphones do not consider the psychoacoustics of the human's hearing system. It is a fact that a human's hearing is binaural [8], which implies a neural connection between two ears. The human's brain integrates sounds between two ears, and the human head can be considered as a "passive" barrier between sounds, received by both ears. Binaural hearing features are widely used in digital hearing aids [2] to improve the quality of the sound and make sound perception more realistic. Unfortunately, commercial noise-cancellation headphones approaches do not pay much attention to binaural techniques. Based on these technical and implementation gaps, there are several enhancements that can be improved:

1. High-frequency noise reduction;

It was mentioned above that ANC algorithms target on the low-frequency range. Therefore, it is possible to integrate other algorithms, based on psychoacoustic analysis [9] to extend the noise control frequency range.

2. The perceptual quality of the music in the presence of the background noise;

The perceptual quality of the audio signal is highly correlated with the features of the human's hearing system. The introduction of psychoacoustic analysis in the sound processing and noise reduction algorithm can help to improve the perceptual quality of the processed audio signal.

3. Noise reduction performance for real-life multiple noise sources scenarios;

The introduction of binaural techniques and sharing noise information between two channels of headphones can improve the noise reduction performance of both channels and makes ANC headphones more efficient for multiple noise sources.

The motivation of this research work is to develop and implement a new noise reduction system for headphones based on the ANC algorithm integrated with psychoacoustic analysis and binaural technique to improve noise reduction performance and perceptual sound quality of commercial noise-cancellation headphones. The aim is to develop a noise reduction system for headphones, which is independent of the number and type of noise sources and will provide high and comfortable quality of sound for users.

1.2 Objectives

With the aim to develop and implement a noise reduction system for headphones based on three main components: ANC algorithm, psychoacoustic analysis, and binaural technique, this thesis focuses on the following objectives.

Firstly, due to the lack of investigations on the integration of human's hearing features to headphones, we focus on psychoacoustic analysis. The human's hearing system perceives sound in different ways [10] according to the environmental conditions, playback quality, etc. Currently, the noise-

cancellation headphones process and reduce all environmental noise signals. However, it is not always necessary. Therefore, a more efficient noise control strategy is to estimate the amount of environmental noise, which is audible in the presence of different target sounds. This investigation leads to the development and implementation of the ANC algorithm, which reduces only audible noise components.

Secondly, it is necessary to find a solution for high-frequency noise reduction. To solve this issue, the psychoacoustic masking algorithm [11] was integrated into the ANC algorithm. The idea is to use music to mask out residual (after ANC) and high-frequency noise components. The objective is to develop and implement an automatic gain control system (AGC) [12] for music to mask out residual noise and without decreasing the perceptual quality of the music signal.

Thirdly, it was decided to investigate the possibility of development and implementation of a binaural ANC algorithm to theoretically and practically prove the assumption that it can do a better job for multiple noise source scenarios. The task is to understand how to implement the connection between two channels, how to define the cases, where the binaural ANC algorithm outperforms the conventional ANC approach and vice versa. As a result, to develop the system, which will automatically select the “best” ANC implementation according to the environmental noise conditions.

Finally, the proposed binaural ANC algorithm is also applied for hearing aids. This step aims to extend the application area of the proposed approach and show that it can be used not only for headphones but also for other two-channel multimedia systems [13].

1.3 Major Contributions of the Thesis

This thesis focuses on the study, development, and implementation of the efficient and universal noise reduction system for headphones based on ANC algorithm, psychoacoustic analysis and masking, binaural technique. The major contributions of the thesis are as follows:

1. *Investigation of existing noise cancellation headphones techniques and the*

introduction of methods to improve noise reduction performance.

Commercial noise-cancellation headphones approaches are investigated. The most commonly used algorithms are found and discussed. The goals are to find and understand the major technical and algorithm's gaps of existing noise cancellation headphones and propose ways and additional techniques to improve noise reduction performance and sound quality of the system.

2. Development and implementation of psychoacoustic subband ANC algorithm by applying psychoacoustic analysis to conventional subband ANC algorithm.

Firstly, the non-uniform subband adaptive filter (SAF) approach is proposed. The most challenging part, implementation of a new weight transformation algorithm for non-uniform filter bank, is implemented using frequency wrapping technique and modification of existing uniform weight transformation approaches. Secondly, critical bands non-uniform filter bank is applied to implement critical band SAF and critical band subband ANC algorithms. Thirdly, psychoacoustic analysis is employed to estimate the portion of audible noise components in the presence of the music in order to apply the ANC algorithm only to the frequency bands with audible noise components. Finally, psychoacoustic evaluations and computational resources measurements are conducted to compare the proposed approach with the conventional ANC algorithm.

3. Introduction of psychoacoustic masking algorithm to improve high-frequency noise reduction.

Active noise control algorithms are not highly efficient for the high-frequency noise. Therefore, in this thesis, the psychoacoustic masking algorithm is integrated into the psychoacoustic subband ANC algorithm. The idea is to use the music signal as a masker to mask out the residual and high-frequency noises. The AGC block is developed to estimate gain coefficients for music's critical frequency bands without the introduction of any distortions and artifacts. Integrated psychoacoustic subband ANC and masking algorithm is compared with other noise reduction approaches in terms of objective and subjective psychoacoustic evaluations to test the

perceptual quality of the final sound outputs.

4. *Development, implementation, and investigation of binaural ANC algorithms for headphones to improve noise reduction performance for multiple noise sources cases.*

Binaural noise reduction (NR) algorithms are widely used in digital hearing aids to improve hearing aids performance and make the sound more realistic. Based on this observation, binaural NR for hearing aids is modified according to ANC algorithm needs and requirements. The connection link between two headphones' channels helps to artificially increase the number of reference microphones and provide more complete environmental noise information for both channels. The proposed binaural ANC algorithm is tested and compared with conventional or bilateral ANC algorithm in terms of noise reduction performance. Results show that the proposed binaural ANC algorithm is efficient for multiple noise sources cases and improves noise reduction performance for both channels.

5. *Investigation and development of combined (bilateral/binaural) ANC algorithm for headphones.*

Comparisons of bilateral and binaural ANC algorithms show that the binaural ANC approach outperforms bilateral one in the most of multiple noise sources cases, however, it is not always better. Therefore, it is decided to find regularities, which can help to define and select the "best" ANC implementation (bilateral or binaural) according to the noise situation. A coherence-based method is proposed and developed with the aim of the "best" ANC approach definition. Finally, a new combined ANC algorithm with bilateral and binaural ANC options is proposed. Simulations and real-time experiments are conducted to validate the performance of the combined ANC algorithm for headphones and the efficiency of the proposed method is proved.

1.4 Organization of the Thesis

This thesis is organized into six chapters. Chapter 1 is an introduction to the main parts of this research work. It consists of motivations, objectives and main contributions. Finally, the structure and organization of the whole thesis are presented. In Chapter 2, a literature review on the previous studies in these fields and related adaptive algorithms are presented. Chapter 3 describes the basics of ANC algorithms, the definition and working principles of the subband ANC algorithm. The advantages of subband ANC algorithms are discussed. Psychoacoustic analysis and features of the human's hearing system are described. A new psychoacoustic subband ANC algorithm is proposed in this chapter. Perceptual quality results of the proposed and conventional methods are analyzed and compared. Chapter 4 is devoted to high-frequency noise reduction. Based on the psychoacoustic model from Chapter 3, integrated psychoacoustic subband ANC and masking system is proposed. The detailed description of the psychoacoustic masking working principles is presented. The automatic gain control block for the music signal is also described in Chapter 4. It is necessary to mask out residual and high-frequency noise components. The proposed integrated system is compared with other noise reduction approaches in terms of psychoacoustic evaluations. Objective and subjective tests are conducted. Chapter 5 describes different binaural techniques with an explanation of the features and advantages of binaural hearing and binaural algorithms. Binaural filtered-x normalized least-mean-square (FxNLMS) algorithm is proposed and described in Chapter 4 with the further integration of this algorithm to the conventional ANC approach. Finally, binaural and bilateral ANC approaches are compared based on real-time experiments. The binaural ANC algorithm does not always outperform bilateral implementation. Therefore, a combined ANC algorithm with bilateral and binaural options is developed and implemented. The proposed algorithm is able to automatically select the "best" ANC implementation. Finally, simulations and real-time experiments' results are shown and discussed in this chapter. Chapter 6 describes the application of the proposed binaural and combined techniques for the hearing aids. Chapter 7 concludes the main results and findings of this thesis.

Chapter 2

Literature Review on ANC and Psychoacoustic Algorithms

Chapter 2 presents the literature review and previous studies related to this thesis. Firstly, the theoretical foundations of ANC algorithms are explained and described. Moreover, existing commercial noise-cancellation headphones are discussed with their noise reduction performances and explanations of their working principles. This thesis describes extension approaches of the conventional ANC algorithm based on the features of the human's hearing system. For this purpose, psychoacoustics of the human's hearing system and binaural algorithms are presented and briefly described in this chapter.

2.1 Description of ANC Algorithm

In this section, the main working principles and basic approaches are discussed. Furthermore, the feedforward ANC algorithm is discussed in detail as a base-module of this work. An integrated audio ANC algorithm from the previous study is reviewed and discussed. Finally, this section presents an overview of existing commercial ANC headphones, and their performances are discussed.

2.1.1 ANC Algorithm Working Principles

Nowadays several audio companies propose headphones with the ability of active noise reduction. Noise cancellation headphones are based on the ANC algorithm. The idea of the ANC algorithm is shown in Figure 2.1. The active noise control algorithm uses electroacoustic systems to cancel environmental noise based on the acoustic superposition principle [14] of the noise signal and noise control signal.

Active Noise Control – Original Idea

Figure 2.1 – Idea of the ANC algorithm [15]

The goal is to produce an anti-noise signal with the same amplitude and opposite phase [16] to the primary noise at the control point or area, which results in the noise attenuation (both signals compensate each other). Noise reduction performance strictly depends on the amplitude and phase accuracy of the noise control signal.

The ANC algorithms are divided into two types: feedforward and feedback [17]. A feedforward ANC algorithm requires a reference sensor, which captures environmental noise before it propagates to the error sensor. A feedforward ANC algorithm is efficient for broadband noise reduction. It has a reference signal, which is correlated to primary noise and provides a time advantage, compared to the error microphone signal, for accurate processing. Feedback ANC algorithm uses only the error sensor. The signal, captured by error sensor, is also used as a system input. Feedback ANC algorithm is useful for narrowband noise reduction. In general, the feedforward ANC algorithm is more robust than feedback implementation. Especially, when the reference sensor is isolated from the secondary source, which does not allow propagation of noise control signal back to the reference sensor.

Moreover, ANC algorithms can be classified into analog or digital

implementation [18]. Most of the real-life ANC applications use analog circuitry because it is cheaper and easier for implementation. However, real-time ANC systems require reliability, highly accurate control and, temporal stability. Therefore, digital signal processing (DSP) [19] systems with a high processing rate, and precision are employed for real-time digital ANC solutions. Moreover, digital signal processors make it easier to develop and implement additional approaches to improve algorithm performance. This thesis focuses on the digital broadband feedforward ANC algorithm, which allows new processing blocks and modify conventional feedforward ANC algorithm to enhance noise reduction and perceptual performance.

2.1.2 Feedforward ANC Algorithm

Figure 2.2 shows the main components and processing blocks of the feedforward ANC algorithm. Here and in this thesis dashed blocks represent the acoustic domain and solid blocks refer to the electrical domain. The feedforward ANC algorithm requires two sensors (microphones): reference and error; and secondary sources (loudspeaker). A reference microphone is used to capture environmental noise (reference signal) $x(n)$, error microphone captures residual noise (error signal) $e(n)$, and the secondary source produces the anti-noise signal $y(n)$.

Figure 2.2 – Feedforward ANC algorithm (dash line indicates acoustic domain)

The goal of the ANC system is to reduce primary noise at the control area around the error microphone position. In general, the ANC block consists of a controller or filter, which processes reference signal $x(n)$ to generate the noise control signal $y(n)$. The performance of the ANC algorithm strictly depends on the primary path ($P(z)$) from the noise source to the error microphone or control point, and the secondary path ($S(z)$) from the control loudspeaker to the error microphone. In the ideal case, the ANC block should approximate an optimal Wiener filter $W_{opt}(z)$ [20], which approximates $P(z)$ and compensates $S(z)$.

$$W_{opt}(z) = \frac{P(z)}{S(z)}. \quad (2.1)$$

However, the optimal Wiener filter can be non-causal [21]. Causality constraint is violated if acoustic and electric delays of the noise control system exceed the acoustic delay of the primary path. To satisfy causality requirements, the group delay of the primary path $P(z)$ should be larger than the group delay of the secondary path $S(z)$. It is noted that the group delay of $P(z)$ includes only acoustic path delay and delay caused by the passive ear cup. However, the group delay of $S(z)$ consists of acoustic path delay and full processing time (ADC and DAC converters, anti-aliasing filters, etc.). The causality depends on noise sources' directions, number of noise sources, noise frequency range and fitting of headphones. In the previous study [22], it was shown that poor or improper fitting of headphones to the ear can cause significant issues for the ANC algorithm: group delay of $S(z)$ increases, the temporal advance of reference microphone's signal concerning the desired signal, etc. Most existing ANC headphones use the fixed filter [23] solution. However, it is hardly possible to get optimal Wiener filters for real-life broadband noise signals. Moreover, the fixed-filter ANC approach is sensitive to the changing of the positions of the reference sensor and secondary loudspeaker.

The adaptive feedforward ANC algorithm [24] was developed to provide a noise reduction solution for instable and highly changeable systems. Headphones are an example of a highly changeable system because of different fitting options and various outdoors noise situations. The adaptive feedforward ANC algorithm is based on an adaptive filter [25], which acts as an approximation of the optimal

Wiener filter in a specific time moment. The block diagram of the adaptive feedforward ANC algorithm is shown in Figure 2.3. Here, $p(n)$ and $s(n)$ are impulse responses of the primary and secondary paths, respectively, and $\hat{s}(n)$ is an impulse response of the estimated version of the secondary path. The area between the microphone and headphones' emitter helps to achieve causality and high coherence between the error microphone signal and the noise to be canceled. The adaptive filter can be implemented as all-zero, pole-zero or all-pole structure. All-zero finite-impulse response (FIR) or transversal filter [16] is typically used for this algorithm. Least-mean-square (LMS) algorithm [26] is the most commonly used adaptive algorithm for ANC applications. The LMS algorithm is a stochastic gradient descent method, which continuously estimates results by updating filter weights, based on the error and reference signals at the current time. The electrical reference signal and error signal are sensed by the reference and error microphones, respectively. Moreover, the noise control signal is produced by an electrical loudspeaker. The ADC/DAC converters, LMS computation time introduce several time delays into the process. Moreover, secondary path transfer function should be compensated to get satisfied noise reduction results. Therefore, the conventional LMS algorithm is not useful for real-life feedforward ANC applications. The error signal $e(n)$ corresponds to the reference signal $x(n+l)$, where l is a time delay of the secondary path. To compensate for the effects of the secondary path, identical $\hat{s}(n)$ filter (estimated version of secondary path $s(n)$) must be added to the reference signal path.

Figure 2.3 – Adaptive feedforward ANC algorithm diagram (dash line indicates acoustic domain)

This approach is called filtered-x LMS (FxLMS) algorithm [27]. The reference signal $\mathbf{x}(n)$ is filtered by an estimated version of the secondary path $\hat{\mathbf{s}}(n)$. To improve the stability of the adaptive process, a normalized version of the FxLMS (FxNLMS) [28] is commonly used. FxNLMS algorithm can be expressed by the following equations:

$$x'(n) = \hat{\mathbf{s}}(n) * \mathbf{x}(n), \quad (2.2)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{e'(n)\mathbf{x}'(n)}{\|\mathbf{x}'(n)\|^2}, \quad (2.3)$$

where $\hat{\mathbf{s}}(n)$ is the impulse response of the estimated secondary path, $\mathbf{w}(n)$ and $\mathbf{w}(n+1)$ are the adaptive filter weights for the current and the next iterations, and $\|\cdot\|$ is the Euclidean norm operator.

There are two ways to get the estimated version of the secondary path $\hat{\mathbf{s}}(n)$: off-line estimation and on-line estimation [29]. On-line estimation measures the secondary path in the specific time moment before passing reference signal $\mathbf{x}(n)$ through it. It is more accurate but, on the other hand, it has a higher computational cost and has an influence on the ANC algorithm processing rate. In this work, we are focusing on the off-line estimation technique, which implies secondary path measurements before the ANC algorithm starts.

Coherence is another basic concept, which helps to analyze ANC algorithm performance. The coherence is a function of normalized cross-spectral density function in the range from 0 to 1.

$$C_{ab}(f) = \frac{|G_{ab}(f)|^2}{G_{aa}(f)G_{bb}(f)}, \quad (2.4)$$

where a and b are two different signals, f is frequency, $G_{ab}(f)$ is the cross-spectral density between a and b , and $G_{aa}(f)$ and $G_{bb}(f)$ the auto-spectral density of a and b .

The ANC algorithm's performance depends on the coherence between the desire and reference signals. High coherence, at the noise frequency range, can guarantee significant noise reduction performance.

To summarize the feedforward ANC algorithm, there are the most significant

statements and points, which have sufficient influence on the algorithm's performance. As was mentioned in previous studies [30] – [31], the ANC algorithm is efficient only for the frequencies up to 1.5 kHz. In [30], the low-frequency efficiency of the ANC algorithm was explained by the difference in wavelength between low- and high-frequency signals. The ANC algorithm can control broadband noise only when causality requirements are satisfied. Otherwise, only narrowband noise can be reduced.

2.1.3 Integrated Audio ANC Algorithm

Active noise control is commonly activated to cancel unwanted noise when listening to music or during a mobile phone conversation. The ANC approach for audio or multimedia devices, equipped by headphones, have several requirements: (i) to cancel ambient environmental noise; (ii) to use headphones emitters to playback both, music and noise-control signal; (iii) do not introduce any distortions and artifacts to the target audio signal. To satisfy these requirements, an integrated audio ANC algorithm [32] was developed. Figure 2.4 shows the block diagram of the feedforward integrated audio ANC algorithm. Feedforward integrated audio ANC algorithm differs from the conventional feedforward ANC approach in the presence of the music or speech, which should not influence the ANC algorithm performance and should not be modified or distorted. The error microphone captures both residual noise signal (error signal) and music/speech signal. Music/speech is subtracted from the error signal in the electrical domain to get an uncorrupted error signal for the FxLMS algorithm. The music/speech signal is passed through the estimated secondary path to compensate for it before subtraction.

Figure 2.4 – Integrated audio feedforward ANC algorithm (dash line indicates acoustic domain)

Feedforward integrated audio ANC algorithm is expressed by the following equations. Noise control signal:

$$y(n) = \mathbf{w}(n) * \mathbf{x}(n), \quad (2.5)$$

$$y'(n) = \hat{\mathbf{s}}(n) * (\mathbf{y}(n) + \mathbf{a}(n)), \quad (2.6)$$

where $\mathbf{w}(n)$ is the adaptive filter impulse response, $\mathbf{x}(n)$ is the reference signal, $\hat{\mathbf{s}}(n)$ is the impulse response of the estimated secondary path and $\mathbf{a}(n)$ is the target audio signal.

The desired signal is expressed as follows:

$$d(n) = \mathbf{p}(n) * \mathbf{x}(n), \quad (2.7)$$

where $\mathbf{p}(n)$ is the impulse response of the primary acoustic path.

The error signals are defined as follows:

$$e(n) = d(n) - y'(n), \quad (2.8)$$

$$e'(n) = e(n) - \hat{\mathbf{s}}(n) * \mathbf{a}(n), \quad (2.9)$$

where $e(n)$ is the error signal, captured by the error microphone (the residual noise + the target music/speech signal) and $e'(n)$ is the residual noise only

signal, after subtraction of the target music/speech signal.

The last stage of the integrated audio ANC algorithm is the FxNLMS algorithm, which is expressed by the equations (2.2) – (2.3). The integrated audio ANC algorithm is useful for headphones ANC applications. Therefore, it is the basis of this work.

2.1.4 Overview of Noise Cancellation Headphones

Nowadays, there are several variations for noise-cancellation headphones from different audio and electronic companies. Figure 2.5 shows the working principle of the ANC headphones. In this work, we focus on the closed-back headphones.

The commercial ANC headphones are based on analog or digital fixed filter solutions. The embedded ANC chipsets are able to provide both feedforward and feedback approaches. However, the feedforward ANC algorithm is commonly used in modern noise-cancellation headphones. The Qualcomm CSR8675 SoC is an example of a feedforward ANC chipset, and it is also a wireless Bluetooth audio applications platform. The feedforward hardware-based ANC technology is integrated into this chip. Because of its small size and wireless technology, Qualcomm CSR8675 SoC is a useful solution for ANC headphones.

Figure 2.5 – ANC headphones [33]

Companies, like Sony and Bose, produce the most popular ANC headphones. Bose was a pioneer company in this area. However, Sony proposed some additional features, such as hearing through technology, and developed its own ANC chipset for the products. Nowadays, ANC technology is introduced for in-ear earphones as well as for closed-back headphones. As was mentioned above, this thesis focuses on closed-back headphones applications. Therefore, we present an overview of the most popular closed-back ANC headphones. Sony WH-1000XM3 and Bose QuietComfort 35 II. The photos of these headphones are shown in Figure 2.6. Both headphones are implemented using wireless Bluetooth technology. A feedforward fixed filter solution is applied for these headphones. Noise reduction performances of these headphones are quite similar. Bose QuietComfort 35 II has an average noise reduction performance of -27 dB. Figure 2.7 shows Bose QuietComfort 35 II noise reduction performance in the frequency domain. Sony WH-1000XM3 has an average noise reduction performance of -29 dB. Figure 2.8 shows the Sony WH-1000XM3 noise reduction performance in the frequency domain. Figures 2.7 and 2.8 show that passive attenuations of headphones' ear cups are similar and start from 500 Hz.

Figure 2.6 - Sony WH-1000XM3; Bose QuietComfort 35 II

The Bose QuietComfort 35 II and Sony WH-1000XM3 headphones are effective for the frequency range up to 1000 Hz. Bose and Sony noise-cancellation headphones are based on bilateral ANC implementation and there is no link to the human's hearing system and connection between two channels.

In general, closed-back ANC headphones are equipped by the reference microphone, situated outside the ear cup, error microphone situated inside the ear cup (for adaptive ANC approach) and headphones' emitters, act as noise cancellation loudspeaker and produce anti-noise signal.

Figure 2.7 – Bose QuietComfort 35 II noise reduction performance [34]

Figure 2.8 – Sony WH-1000XM3 noise reduction performance [35]

Most of the existing commercial ANC headphones are based on bilateral [10] implementation, which implies that two independent monaural [35] ANC algorithms are applied for the left and right channels, respectively. Moreover, there are commercial ANC headphones, which use only one reference microphone, outside one of the ear cups, and apply it for both channels to lower the components cost. Based on the discussed observations, this thesis focuses on adaptive feedforward ANC solution for headphones with connection and sharing noise information between two channels to improve noise reduction performance of existing ANC approaches for headphones.

2.2 Psychoacoustic Analysis and Masking

This section describes the psychoacoustics of the human's hearing system and masking principles [36]. This section begins with a description of the human's hearing system. The main parts of the hearing system are shown and their roles are explained. The following subsection focuses on the principles of psychoacoustic masking. Temporal and frequency masking approaches are discussed. Different masking types and their properties are presented. This section also discusses the ANC algorithm and psychoacoustic masking integration, based on the previous work.

2.2.1 Human's Hearing System

Psychoacoustic analysis [37] helps to explore and approximate the human's hearing system. There are many applications where psychoacoustic analysis can be applied. Commonly, the psychoacoustic analysis represents audio signals in terms of the human's perception of sound. The human's hearing system is a complex system, which consists of several strictly connected sub-systems. A simple scheme of the hearing system is shown in Figure 2.9.

Figure 2.9 – Human's hearing system [38]

The outer ear, middle ear, and inner ear are three major parts of the human's hearing system. These parts are classified according to their functionality. The outer ear captures and transmits sound energy to the ear canal and further, to the eardrum. The length of the ear canal is about 2 cm, which corresponds to the quarter of the 4 kHz wavelength. This explains that the most sensitive frequency range of human's hearing system is about 4 kHz

The middle ear has several important functions. It produces oscillation of fluids and can be divided into smaller functional units. Eardrum acts as a sound pressure receiver and operates on the broad frequency range. Hard bone produces motions of the eardrum, which are transmitted to the inner ear by the middle ear ossicles.

The middle ear is closed off from the environment by eardrum membrane at the one side and by eustachian tube at another. The eustachian tube operates like an equalizer. It connects with the upper throat, which is responsible for external pressure influence. External pressure differences cause changes in the eardrum position and equalize sound according to the environmental situation.

The inner ear plays the most important role in sound perception. Cochlear is the second name of the inner ear. Therefore, an approximation of cochlear is commonly used to represent sound in terms of human's perception. Cochlear has a snail shape. Figure 2.10 shows a schematic representation of cochlear.

Figure 2.10 – Human's cochlear [39]

Hair cells of different lengths cover the cochlear area. They are responsible for the perception of the sound of different frequencies. Each cell is excited by sound vibrations of a specific frequency range. In other words, hair cells form a non-uniform specific frequency bands, called Barks or critical bands [40], filter bank. Critical bands' properties vary in terms of perceptual evaluations: loudness, sharpness, roughness and audible threshold. Audible or hearing threshold defines the energy level of sounds of different frequencies, above which sound becomes audible for the human's hearing system. The hearing threshold is not always fixed. It depends on several factors, such as environmental conditions and individual hearing abilities of a person.

The absolute threshold of hearing (ATH) [41] is a function of frequency, which defines an audible level of sound in dB terms in a quiet environment. Figure 2.11 shows the ATH of the average human, together with the threshold of pain and the most sensitive frequency range (yellow block). Zwicker [42] defined ATH by the following math approximation equation:

$$ATH(f) = 3.64 \left(\frac{f}{1000} \right)^{-0.8} - 6.5 e^{-0.6 \left(\frac{f}{1000} - 33 \right)^2} + 10^{-3} \left(\frac{f}{1000} \right)^4, \quad (2.10)$$

where f is the frequency in Hz.

In general, music or speech signals do not exceed 10 kHz frequency and 100 dB energy level. The threshold of pain, which can be dangerous and harmful for the hearing system, is about 120-140 dB for broadband sounds.

Figure 2.11 – Hearing thresholds [42]

As was mentioned above, 2 – 4.5 kHz is the most sensitive range of the hearing system, which corresponds to the properties of the ear canal.

Bekesy-tracking method [43] is used to estimate the individual hearing threshold. It is a medical test, which is based on the slow changing of frequency and energy level to define the audible level of different frequencies for a person.

2.2.2 Principles of Psychoacoustic Masking

A low sound pressure level (SPL) [44] sound is audible when it is single. However, it becomes inaudible in the presence of other sounds with higher SPL. Such a phenomenon is called acoustic masking [45]. High SPL sound, called masker, makes low SPL sound, called maskee, inaudible. Masker modifies ATH to create its masking threshold. The masking threshold defines the influence of the masker on the maskee sounds. The modified masking threshold is always higher than the ATH in quiet. However, if the frequency contents of masker and maskee differ a lot, the masking threshold can repeat ATH for maskee frequency range.

There are two types of psychoacoustic masking: frequency and temporal masking [42]. Temporal masking is based on the time of masker and maskee

appearance. The short-time low SPL sound is inaudible if it appears during the presence of the long-time high SPL sound. Temporal masking is mostly independent of the frequency content of sounds. It can be effected only by a sound level, its duration and time of appearance. Temporal masking is divided into three types according to the time of appearance. Simultaneous masking is the most common case. The loud masker and soft maskee appear at the same time. The simultaneous-type masking threshold is flat and has a small SPL variance (almost fixed). Another type of temporal masking is pre-masking. Masker partially masks out soft maskee if it appears after maskee. Pre-masking occurs only in the time moment near the appearance of the masker. Pre-masking can be felt in about 20 ms before masker sound appears. Post-masking is similar to the pre-masking. However, loud masker masks out the maskee even after the stopping of maskers. The post-masking effect depends on the duration of the masker, but there is an average performance of post-masking. The masking threshold of masker decreases after 5 ms and acquires the same level as the absolute hearing threshold in quiet after 200 ms from masker stopping. Figure 2.12 shows the time areas of temporal masking.

The temporal masking is important for acoustic processes. However, there is not any general model, which defines and estimates temporal masking. Therefore, the focus of this work is on frequency masking. Several psychoacoustic models are useful for frequency masking estimation and make it applicable for different goals.

Figure 2.12 – Principles of temporal masking [42]

2.2.3 Frequency Masking Approach

Maskers are divided into two basic types: tone-like maskers and noise-like maskers. The same SPL noise-like masker threshold and tone-like masker threshold have different properties. The noise-like maskers are classified into two types: broadband and narrowband maskers. As an example, white noise is a typical broadband masker. The masking threshold of white noise is similar for all frequencies before 500 Hz, and the threshold rises for frequencies above 500 Hz [42]. The white noise masking threshold for very low and very high frequencies repeats ATH. In general, broadband maskers are characterized by the linear behavior of the masking process.

The narrowband maskers are defined as signals with a frequency range less than the analyzed critical bandwidth. Low-frequency narrowband masker's threshold covers a wider frequency range than high-frequency masker of the same SPL. The maximum level of masking threshold tends to be lower for high-frequency narrowband masker and to be higher for low-frequency narrowband masker. These properties of narrowband maskers are noticeable in Figure 2.13. Three narrowband maskers with different center frequencies (250 Hz, 1 kHz, and 4 kHz) have SPL of 60 dB. The dashed line represents ATH. It is obvious that the masking threshold of 250 Hz narrowband masker is the widest and has the highest level.

The shape of the masking threshold depends on the SPL of the masker. Higher SPL masker produces a wider masking threshold and it influences the wider frequency range. This phenomenon is shown in Figure 2.14. The same frequency but different SPL narrowband maskers have a nonlinear shape of the masking threshold. Masking thresholds have a very steep rise from low frequencies to center frequency before the maximum level is reached. The slope of this rise is mostly independent of SPL value. However, at higher maskers' levels the slope towards high frequencies become increasingly small. Therefore, the masking threshold of narrowband masker has nonlinear SPL dependence.

Figure 2.13 – Masking thresholds of narrowband maskers [42]

Figure 2.14 – Masking thresholds of 1 kHz center frequency masker with different SPL [42]

Tone-like masker [46] is another type of maskers. Tone-like maskers are able to mask out other tones and soft noise signals. The idea is similar, a single tone of high SPL makes other tones of neighboring frequencies inaudible. Figure 2.15 shows the tone-by-tone masking process. Single-tone masker modifies ATH and the masking curve covers two soft tones of neighboring frequencies, which implies that the soft tones become inaudible.

Figure 2.15 – Tone-by-tone masking [42]

Real-life sounds often consist of multiple harmonics [47] and the fundamental frequency range [48]. The number of harmonics has a significant influence on the masking ability of sound. Figure 2.16 shows an example of the masking threshold of a fundamental 200 Hz tone of 40 dB SPL and 60 dB SPL and an additional 9 harmonics. The dips between harmonics become smaller with frequency increasing, which shows that the masking threshold is flatter for the high-frequency maskers. The psychoacoustic masking has found its application [49]-[50] in various areas. It appears to be an efficient and powerful approach for environmental noise reduction. It is assumed that the target sound should mask out environmental noise in noise reduction applications.

Figure 2.16 – Masking threshold of multiple harmonics [42]

The psychoacoustic analysis is used to estimate gain coefficients for each critical band of the target sound to cover noise by the masking threshold. It works as an audio equalizer but with the aim to reduce noise audibility. However, there are significant disadvantages of such a method of noise reduction as a single, independent approach. The level of environmental noise can be high, and unlimited audio amplification [51] can cause a dangerous level of sound for the human's hearing system. With some limitations on amplification being introduced, loud noise cannot be masked. Moreover, it is possible to encounter such a situation when the target sound has not any matches with noise in terms of frequency content. Therefore, the target sound cannot mask out environmental noise. According to all these facts, it was decided to implement the integration of ANC algorithm and psychoacoustic masking to achieve better results of noise reduction and solve the disadvantages of both methods

2.2.4 ANC Algorithm and Masking Integration

The integration of the ANC algorithm and psychoacoustic masking, where environmental noise and audio signals are processed both in acoustic and electrical domains, was proposed in [52]. The narrowband feedforward ANC algorithm was used in this work. The idea is based on the selection of the most suitable and efficient pre-recorded masker signal. Masker selection is implemented according to noise situation. Maskers meet the following requirements: it should be pleasant for the listener and it should be played at the lowest possible loudness but provides high masking performance. However, the ANC and masking algorithms are quite independent and, so far, have not been widely integrated. The ANC algorithm operates as a main noise reduction approach and the masking algorithm selects and applies masker according to residual noise. Figure 2.17 shows the diagram of the ANC algorithm and masking integration. The pre-recorder audio signal $r(n)$ is used as a masker and selected based on the comparison circuit information.

Figure 2.17 – ANC algorithm and masking integration (dash line indicates acoustic domain)

The working principles of this algorithm can be expressed by the following equations:

$$e(n) = y'(n) + d(n), \quad (2.11)$$

$$e'(n) = e(n) - g \mathbf{r}^T(n) \mathbf{p}_2(n), \quad (2.12)$$

where $\mathbf{r}(n) = [r(n) \ r(n-1) \ \dots \ r(n-P+1)]^T$ is the masker (recorded audio) vector, $g \cdot \mathbf{r}(n)$ is the amplifying audio signal, $\mathbf{p}_2(n)$ is the impulse response of the filter to compensate electrical path from error microphone to the comparison circuit.

Residual noise is used to update coefficients of an adaptive filter, using the LMS algorithm.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e'(n) [\mathbf{x}^T(n) - g \mathbf{r}^T(n)] * \hat{s}(n). \quad (2.13)$$

The main problem faced in this approach is that sampling frequency used in a narrowband ANC algorithm is rather low, about a few kHz. It can be mismatched between the sampling frequency of the noise and the masker. Another issue of this approach is the necessity of prior knowledge of masker, which makes the system not useful for headphones applications.

2.3 Binaural Algorithms

This section presents binaural algorithms. Description of the binaural hearing is the first part of Section 2.3. The advantages of binaural hearing are explained based on previous studies. The next sub-section introduces binaural noise reduction algorithms. Binaural noise reduction approaches are commonly used in hearing aids applications. The basics of binaural noise reduction approaches are described in the last part of this section.

2.3.1 Binaural Hearing

The human's hearing system is binaural [53]. Binaural hearing assumes that people use two ears to capture the sounds of the environment. The brain acts as a connector between two ears and processes captured sounds to define the differences between them. Figure 2.18 shows the scheme of binaural hearing. Binaural hearing helps to localize the different sound sources at the same time and helps to focus on the desired sound sources. The binaural hearing has several important abilities in sound perception.

Figure 2.18 – Scheme of binaural hearing; A1 – primary auditory cortex, IC – inferior colliculus, CL – cochlea, AN – auditory nerve, SO – superior olivary complex [8]

The loudness perceived by two ears is higher than for the one ear case. That leads to the binaural loudness summation advantage [35]. Binaural minimal audible field threshold is about 6 dB lower than the monaural threshold. Thus, a human can perceive lower level sounds, binaurally compared to monaural listening.

The most important advantage of binaural hearing is sounds' localization, which leads to spatial hearing. Brain defines the difference between the left and right ear sounds through two major cues: interaural time differences (ITDs) and interaural level differences (ILDs) [54]. ITD and ILD help to localize the sound in terms of the horizontal angle and azimuth. ILD is caused by the head-shadow effect [55]. Therefore, ILD is more effective for high-frequency sounds (above 1500 Hz) because low-frequency wavelength is much longer than the head size. ITD is more useful for low-frequency sounds. On average, maximum ITD is about 690 ms, when the sound source is close to one ear [45]. However, humans' heads are not the same size. Therefore, ILDs and ITDs can vary among individuals. Moreover, the head, torso and ear canal modify the primary sound. In order to model individual binaural processes, the acoustical transfer functions, from free-field to the eardrums, are measured for multiple directions. These measurements are conducted by placing microphones inside the human ears' canal or ears of the dummy head. These acoustical transfer functions are called head-related transfer functions (HRTFs) [56]. HRTFs are widely used for headphones technologies to get a more realistic 3D sound perception.

Binaural masking level difference (BMLD) [57] is the next advantage of binaural hearing. BMLD helps us to perceive and recognize the desired sound in the presence of other background sounds. BMLD can be divided into four main scenarios. The first scenario is monaural masking when both desired sound and masker noise are perceived at only one ear (the right, for example), as shown in Figure 2.19. The desired tonal sound is inaudible in this case because sounds' information comes only from one ear and the brain cannot separate them and focus on tonal sound.

Figure 2.19 – Monaural masking situation (tonal sound is the desired and broadband noise is masker) [57]

However, if masker noise is perceived at the left ear, the desired tone becomes audible. This case is called dichotic condition, as shown in Figure 2.20. The brain receives information from both ears and the desired sound is presented only at the right side, which helps to separate sounds.

However, if the desired tonal sound is added to the left ear, too. Dichotic condition changes to diotic (Figure 2.21). Both sounds are presented at both ears with the same phases and levels. Thus, the brain is not able to detect any differences and the desired tone becomes inaudible. To make the desired tone audible again, it is necessary to turn the tone's phase by 180° and return to the dichotic condition. In this case, sounds' information is different at both ears and tonal sound can be highlighted by the brain (Figure 2.22).

Figure 2.20 – Dichotic condition (tonal sound is the desired and broadband noise is masker) [57]

Figure 2.21 – Diotic condition (tonal sound is the target and broadband noise is masker) [57]

Figure 2.22 – Dichotic condition (tonal sound is the desired and broadband noise is masker) [57]

Several features of binaural hearing are used in digital signal processing algorithms and applied in commercial multimedia devices. The gaming industry widely applies binaural techniques to get a more realistic feeling of the VR/AR [58] games and applications.

2.3.2 Binaural Noise Reduction Techniques

Binaural algorithms are developed and implemented for several different application areas. They are widely used for 3D sound [59] algorithms. Binaural masking level difference and ITD/ILD cues are used to solve cocktail party problems [41] and in the development of directional microphones [60].

The major research question of this thesis is noise reduction algorithms. Thus, binaural noise reduction techniques are discussed in detail. In [41], H. Huang and C. Kyriakakis proposed a modified spectral subtraction algorithm based on the binaural and psychoacoustic analysis. Spectral subtraction [61] is a commonly used noise reduction technique for hearing aids applications. The idea is to subtract the noise spectrum from the mixed noise+speech signals. The noise spectrum is estimated during quiet periods of speech according to the voice activity detector (VAD) [41].

H. Huang and C. Kyriakakis replaced the conventional VAD by the simplified binaural model, which uses BMLD features for better and more accurate estimation of speech sound based on both channels' information. Moreover, the psychoacoustic analysis was applied to get perceptually motivated spectral subtraction. As a result, only audible noise components are subtracted from the

mixed-signal, which helps to introduce fewer distortions to the speech signal. Results showed that the proposed noise reduction algorithm improves the quality of speech and reduces audible background noise components.

T. J. Klasen et al. [62] proposed a binaural noise reduction technique for a multichannel Wiener filter [63] approach. The idea is to share Wiener filter inputs of both channels between each other. The sharing of inputs acts as a link between channels, which provides additional information about noise and desired sounds. Each channel consists of the microphone array to capture environmental sound. Wiener filter estimates the noise of the m -th microphone pair (one from each channel). Subsequently, Wiener filter outputs are subtracted from the mixed noise+speech signal. The block diagram of the binaural multichannel Wiener filter noise reduction algorithm for two channels is shown in Figure 2.23.

Figure 2.23 – Binaural multichannel Wiener filter noise reduction algorithm [62]

The signals captured by microphones are expressed as follows:

$$y_{L_m}(n) = x_{L_m}(n) + v_{L_m}(n), \quad (2.14)$$

$$y_{R_m}(n) = x_{R_m}(n) + v_{R_m}(n), \quad (2.15)$$

where m is the number of microphone pairs, $x(n)$ is the target speech and $v(n)$ is the noise.

The following equations are presented for the left channel. Similar equations are stated for the right channel. The estimated speech signal is expressed as follows:

$$\tilde{x}_{L_m}(n) = (x_{L_m}(n) + v_{L_m}(n)) - \tilde{v}_{L_m}(n), \quad (2.16)$$

where $\tilde{v}(n)$ is the estimated noise signal (Wiener filter output).

Each microphone input has its filter of N taps.

$$\mathbf{w}_{L_m}(n) = [w_{L_m}^0 \ w_{L_m}^1 \dots w_{L_m}^{N-1}]^T. \quad (2.17)$$

The filters' weights of both channels are also shared to get joint binaural filters. Therefore, the binaural filter is formed as a $2MN$ stacked vector:

$$\mathbf{w}_{Left}(n) = [\mathbf{w}_{L_1}^T(n) \dots \mathbf{w}_{L_M}^T(n) \mathbf{w}_{R_1}^T(n) \dots \mathbf{w}_{R_M}^T(n)]^T. \quad (2.18)$$

The input signal is formed in a similar way:

$$\mathbf{y}(n) = [\mathbf{y}_{L_1}^T(n) \dots \mathbf{y}_{L_M}^T(n) \mathbf{y}_{R_1}^T(n) \dots \mathbf{y}_{R_M}^T(n)]^T. \quad (2.19)$$

The filters are implemented to minimize the left and right error signals:

$$E\left\{\left|\mathbf{y}^T(n)[\mathbf{w}_{Left}(n)\mathbf{w}_{Right}(n)] - [v_{L_m}(n)v_{R_m}(n)]\right|^2\right\}, \quad (2.20)$$

where $E\{\}$ is the expectation operator.

The filters, which achieve the minimum value of the cost function, approximate the optimal Wiener filters:

$$[\mathbf{w}_{WF_{Left}}(n)\mathbf{w}_{WF_{Right}}(n)] = E\{\mathbf{y}(n)\mathbf{y}^T(n)\}^{-1}E\{\mathbf{y}(n)[v_{L_m}(n)v_{R_m}(n)]\}. \quad (2.21)$$

The proposed binaural multichannel Wiener filter noise reduction approach shows improvements in the noise reduction performance, especially for multiple

noise sources cases, by 5-7 dB.

Binaural noise reduction algorithms can be applied for two channels systems, which have strong influence or work in the collaboration with human's hearing system. It is noted that the described binaural noise reduction is implemented for hearing aids. However, the binaural technique can be applied for ANC headphones and digital hearing aids, as a main noise reduction algorithm. Based on the previous studies [62]-[63], it is possible to assume improvements in noise reduction for the ANC systems. It is necessary to note that both described algorithms cannot be directly applied for ANC approaches. The ANC algorithms strictly depend on the acoustic primary path and on the acoustic and digital secondary path, which are not taken into account in the described binaural noise reduction techniques. Moreover, these algorithms are not suitable for headphones applications because headphones require to reduce all environmental signals and produce only the sound from headphones emitters.

2.4 Conclusions

This chapter presented a literature review of the basic approaches and previous studies related to this thesis. The major topics of this work are the ANC algorithm, human's hearing system, psychoacoustic masking, and binaural techniques. According to the previous studies, it was shown that current noise reduction techniques and approaches are efficient. However, there are many drawbacks and disadvantages of these methods for headphones applications. The idea of this work is to fill the technical and algorithmic gaps in headphones noise reduction systems, described in this chapter. The following chapters are based on a modification of the previous studies and new algorithms and systems are proposed for headphones noise reduction applications.

Chapter 3

Psychoacoustic Subband ANC Algorithm

This chapter proposes a psychoacoustic subband ANC algorithm. It is obvious that the environmental noise is partially masked by the target sound in headphones applications. Therefore, it is reasonable to focus on and reduce only audible noise components. Such an approach can reduce the computational cost of the noise reduction system. The psychoacoustic features of the human's hearing system are integrated into the conventional subband ANC algorithm. The major contribution of this chapter is a new non-uniform subband adaptive filter, which operates in the critical bands. The proposed non-uniform subband adaptive filter is further applied for the psychoacoustic ANC algorithm, which reduces only the audible noise components. Experimental results prove the efficiency and advantages of the proposed algorithm.

3.1 Subband ANC Algorithms

This section introduces a subband adaptive filter and its applications. Firstly, existing types of subband adaptive filters are described. The subband adaptive filter structures are analyzed and discussed according to the ANC algorithm needs. Furthermore, this section presents and explains the working principles of the subband ANC algorithm. Finally, the advantages and disadvantages of the subband ANC algorithm are discussed in this section.

3.1.1 Subband Adaptive Filter

An adaptive filter is the main processing block of the adaptive ANC algorithms. However, broadband ANC algorithms suffer from the high-order adaptive filters.

There is a tradeoff between the convergence rate and computational burden, from the one side, and noise reduction performance, from another side. The high-order adaptive filter can guarantee a good approximation of the desired signal, however, its convergence rate can be slow. Moreover, a slow adaptation process can cause a causality issue by increasing the secondary path group delay for the ANC applications. Subband adaptive filter (SAF) [64] was developed to reduce the convergence rate and save the performance of fullband adaptive filter. The idea of SAF is to divide the filter input signal and error signal into narrow frequency subbands, using an analysis filter bank, and update filter weights for each band independently. Narrowband subband signals can be better and faster approximated by the adaptive filter, compare with broadband signals. Moreover, bandwidth decreasing allows to introduce a decimation factor [65] and decrease the order of SAF, which leads to faster convergence.

Subband adaptive filters can be classified into two types: open-loop and closed-loop structure [66]. Open-loop structure minimizes subband error signals independently and forms a fullband error signal using a synthesis filter bank. Figure 3.1 shows the open-loop structure of SAF. The $\mathbf{h}_m(n)$ is the subband analysis filter bank, $\mathbf{f}_m(n)$ is the subband synthesis filter bank, $\mathbf{w}_m(n)$ is the subband adaptive filters, M is the number of subbands, $x(n)$ is the input signal, $d(n)$ is the desired signal, $e(n)$ is the fullband error signal, D is the decimation factor.

Open-loop SAF updates subfilters weights in its adaptive loop to minimize local mean square error (MSE) [67] for each subband. Global MSE can be expressed by the following equation:

$$J_{SB} = \sum_{m=0}^{M-1} E\{|e_m(n)|^2\}, \quad (3.1)$$

where $E\{\}$ it the math expectation operator, $||$ is the absolute value operator. The closed-loop SAF structure is shown in Figure 3.2. Unlike open-loop SAF, closed-loop structure minimizes fullband error signal and global MSE is used as a cost function.

Figure 3.1 – SAF open-loop structure

Therefore, closed-loop SAF is more suitable for ANC applications due to the aim of fullband error minimization.

However, conventional SAF suffers from the delay caused by the analysis-synthesis loop. Delay can be expressed by the following equation:

$$\Delta = \left\lfloor \frac{L-1}{D} \right\rfloor D, \quad (3.2)$$

where D is the decimation factor, L is the length of the analysis filter, $\lfloor \cdot \rfloor$ is the integer part of the argument.

In ANC applications, it is not possible to artificially introduce the same delay in the desired signal, because it propagates in the acoustic plant. According to these needs, delayless closed-loop SAF was proposed in [68]. Delayless SAF reduces the synthesis filter bank and divides whole processing into two parallel branches. Subfilters' weights are still updated in the subbands but the filtering process takes part in the fullband at the same time and operates on the fullband input signal.

Figure 3.2 – SAF closed-loop structure

Figure 3.3 shows the block diagram of delayless SAF. Weight transformation block transforms subbands filters' weights to the fullband filter's weights. There are several techniques of transformation algorithms [69] – [70]. However, the fastest and the most commonly used approaches are based on FFT. The delayless SAF requires a non-critically decimated DFT-modulated filter bank. DFT filter bank consists of M complex-modulated bandpass filters $\mathbf{h}_m(n)$. The impulse responses of $\mathbf{h}_m(n)$ and $\mathbf{h}_{M-m}(n)$, for $m = 1, 2, \dots, M/2-1$, are complex conjugates. Thus, only $M/2 + 1$ bands are needed in the transformation algorithm for real-valued signals. Assuming that N is the order of fullband adaptive filter, $N_s = N/D$ is the order of SAFs, and D is the decimation factor, the weight transformation algorithm can be described by the following steps:

Step 1: Transformation of subfilters weights $\mathbf{w}_m$ into DFT-domain by N_s -point FFT for $m = 0, 1, \dots, M/2$.

Step 2: The $N_s \times (M/2+1)$ DFT weights are stacked to form the first $N/2$ points of N fullband weights. The vector of fullband weights is completed by adding $(N/2)$ -th element, which is equal to zero. Using the complex-conjugate values of 1 to $N/2-1$ weights in reversed order as the values of $N/2+1$ to $N-1$ weights. Finally, fullband filter weights are transformed in the time domain by IFFT operation.

Figure 3.3 – Delayless closed-loop SAF

3.1.2 Subband ANC Algorithm

The subband ANC algorithm [71]-[72] was developed to achieve a faster convergence rate. Delayless SAF is applied to an integrated audio ANC algorithm to increase the convergence rate of the system. The block diagram of the subband integrated audio ANC algorithm is shown in Figure 3.4. Subband ANC algorithm achieves a faster convergence rate because the bandwidth of subband noise is narrow, which leads to the narrow-band ANC case and allows to use of low-order subband adaptive filters.

The filter bank input $x'(n)$ and error signal $e'(n)$ are two inputs of the SAF. Both signals are divided into subbands and decimated according to the decimation factor. Subband filters' weights are passed through a weight transformation algorithm to get a fullband filter, which operates on the reference signal to get a fullband noise control signal. As was mentioned above, such an approach helps to minimize global (fullband) error of whole frequency range primary noise.

Figure 3.4 – Subband integrated audio ANC algorithm

Due to the DFT-modulated filter bank is used in this work, filter bank outputs are complex values. Therefore, the subband FxNLMS algorithm has modifications according to the complex inputs. Moreover, FxNLMS algorithm updates filters' weight only for half of the band, as was explained above.

$$\mathbf{w}_m(n+1) = \mathbf{w}_m(n) + \mu \frac{\mathbf{x}'_m(n) e'_m(n)}{\|\mathbf{x}'_m(n)\|^2}, \quad (3.3)$$

where m is the number of the subband, $*$ is the complex conjugation operation, $\mathbf{x}'_m(n)$ is the subband FxNLMS input $\mathbf{x}'_m(n) = [x'_m(n), x'_m(n-1), \dots, x'_m(n-N_s+1)]^T$, N_s is the subband filter order.

The subband ANC algorithm uses all advantages of the delayless SAF. Filtering procedure and generation of the noise-canceling signal take part in the fullband. However, the subband filters' weights updating procedure operates in each band independently and at the same time with filtering. The subband ANC algorithm is the main core of the proposed psychoacoustic subband ANC algorithm [73]. However, before we begin to explain the proposed psychoacoustic ANC algorithms, the next subsection starts with the discussion and explanation of critical bands and critical bands filter bank.

3.2 Description of the Psychoacoustic Subband ANC Algorithm

This section begins with the description and approaches of critical bands filter bank implementation. Different methods of conversion from uniform to non-uniform filter banks are discussed. Major ideas of the psychoacoustic subband ANC algorithm are presented. Finally, a new weight stacking algorithm for non-uniform subband SAF and psychoacoustic ANC algorithm are proposed and discussed.

3.2.1 Critical Bands Filter Bank

Cochlear is the basic part of the human's hearing system, which is responsible for sound perception. Therefore, the psychoacoustic analysis starts with the approximation of the cochlear. Critical bands of cochlear are non-uniform. Therefore, critical bands can be approximated by the non-uniform filter bank, which is applied to the signal before further analysis. In [42], Zwicker proposed a math model to define critical bands number and the bandwidth according to the frequency in Hz. The transformation from the Hz-frequency scale to the Bark scale is expressed by the following equation:

$$v = 13 \arctg\left(\frac{f}{1000}\right) + 3.5 \arctg\left(\frac{f}{7500}\right)^2, \quad (3.4)$$

where v is the number of the critical band (Bark) and f is the frequency in Hz.

The bandwidths of the critical bands are defined as follows:

$$CBW(f) = 25 + 75 \left[1 + 1.4 \left(\frac{f}{1000} \right)^2 \right]^{0.69}. \quad (3.5)$$

Table 3.1 shows 25 critical bands correspond to the 44.1 kHz sampling frequency of digital systems. The non-uniform critical bands filter bank is a useful approach to represent the signal in the Bark scale for further subband processing and psychoacoustic analysis.

Table 3.1 Critical bands

Number of Critical Band	Frequency Range, Hz
1	0 - 86.1
2	86.1 - 172.3
3	172.3 - 258.4
4	258.4 - 344.5
5	344.5 - 430.7
6	430.7 - 516.8
7	516.8 - 689.1
8	689.1 - 861.3
9	861.3 - 1033.6
10	1033.6 - 1205.9
11	1205.9 - 1378.1
12	1378.1 - 1722.7
13	1722.7 - 2068.2
14	2068.2 - 2411.7
15	2411.7 - 2756.3
16	2756.3 - 3100.8
17	3100.8 - 3445.3
18	3445.3 - 4134.4
19	4134.4 - 4823.4
20	4823.4 - 5512.5
21	5512.5 - 6890.6
22	6890.6 - 8268.8
23	8268.8 - 11025
24	11025 - 16537.5
25	16537.5 - 22050

There are several techniques to obtain a non-uniform filter bank [74]-[75]. The fastest and the most accurate is the transformation from polyphase uniform DFT-modulated filter bank [76] to the non-uniform filter bank. The transformation can be implemented by the frequency warping method [77]. The idea is to replace delay blocks (z^{-1}) in the polyphase DFT-modulated filter bank implementation by the all-pass phase filters, which modify the shape and bandwidth of subbands. Figure 3.5 shows the block diagram of the transformation process.

All-pass phase filter is expressed as follows:

$$H_{ap}(z) = \frac{z^{-1} - \alpha}{1 - \alpha z^{-1}}, \quad (3.6)$$

where α is the phase parameter.

Phase filters do not influence the signal amplitude, but it changes the phase of the signal components and the phase characteristics of the phase filter is a non-linear function of frequency. Phase parameter α is responsible for the frequency warping process. The parameter α defines the nonlinearity of the phase characteristic. The phase parameter should be accurately estimated to get the target non-uniform DFT-modulated filter bank. This parameter expresses the modified frequency and maps uniform subbands to the target non-uniform subbands template by shaping and resizing of their bandwidths. The valid values of the phase parameter are quite flexible. It can be real- or complex-values. It depends on the target non-uniform filter bank. However, phase filter is stable in the case, when $|\alpha| < 1$. Figure 3.6 shows examples of the frequency warping transformation method. Figure 3.6a shows transformation with real-value negative phase parameter -0.5. This phase parameter transforms uniform filter bank into non-uniform with half-decreasing bandwidths. Figure 3.6b shows transformation with complex-value phase parameter to make mirror filter bank. In the previous study [78], the phase parameter for non-uniform critical bands filter bank was estimated. It is expressed by the following equation:

$$\alpha = 1.048 \sqrt{\frac{2}{\pi} \arctan(0.07212 fs)} - 0.1957, \quad (3.7)$$

where fs is the sampling frequency.

The value of the phase parameter is 0.7452 for the 25 critical bands digital systems with 44.1 kHz sampling frequency. Finally, the non-uniform critical bands filter bank is implemented according to the needs of this research project.

Figure 3.5 – Uniform to non-uniform filter bank transformation

Figure 3.6 – a) Frequency wrapping transformation with real-value phase parameter;
b) Frequency wrapping transformation with complex-value phase parameter;

Low-pass finite impulse response (fir) filter [79] is used as a low-pass prototype filter for a polyphase DFT-modulated filter bank. The order of the prototype filter is 128 taps. The result non-uniform critical bands filter bank is shown in Figure 3.7.

Figure 3.7 – Critical bands filter bank (25 critical bands)

3.2.2 Non-uniform Critical Bands Subband Adaptive Filter

In this section, new critical bands subband adaptive filter [73] is proposed. As was mentioned above, delayless SAF is used for the subband ANC algorithm in this work. Therefore, it requires only the analysis of the critical bands filter bank, which was described in the previous subsection.

At this stage of the work, the following system setups are used. The sampling frequency is 44.1 kHz, which corresponds to the 25 critical bands and frequency range 0-22050 Hz. The order of fullband filter is 1024 taps.

In the uniform SAF systems, each subband contributes the same number of the weights and they are uniformly distributed on the fullband frequency range. Uniform subbands frequency resolutions are the same and it is possible to introduce the same decimation factor for each band that cannot be more than a number of bands. The weights number, which is contributed per band, is possible to estimate by the following equation:

$$N_s = \frac{N}{M}, \quad (3.8)$$

where N is the fullband filter order and M is the number of subbands.

Weight stacking algorithms for uniform SAFs are quite simple and obvious.

However, there is not an algorithm, which allows using a non-uniform filter bank for SAF. Non-uniform filter bank's subbands have different frequency resolutions and bandwidths. Therefore, non-uniform bands contribute different numbers of weights to form a fullband filter. In order to solve this issue, it was decided to implement a weight stacking algorithm for non-uniform SAFs [73]. In fact, it is very complicated to develop a universal weight stacking algorithm for non-uniform SAF because different filter banks can significantly vary. However, it was developed and implemented the weight stacking algorithms for non-uniform SAFs with pre-defined filter bank with known subbands frequency boundaries and their number in advance. The non-uniform weight stacking algorithm is based on the FFT-1 method for uniform filter bank. Critical bands filter bank was defined in the previous subsection and the subbands frequency boundaries are shown in Table 3.2.

FFT-1 method stacks subband weights in the frequency domain as was described in Subsection 3.1.1. Therefore, the first step is to transform subband adaptive filters' weights to the frequency domain using the FFT procedure. The proposed weight stacking algorithm for non-uniform SAF starts with the definition of the frequency step size (resolution) of fullband adaptive filter:

$$step = \frac{fs}{N} = \frac{44100}{1024} \approx 43.07(Hz), \quad (3.9)$$

where fs is the system sampling frequency and N is the fullband filter order.

The major stage of the proposed algorithms is similar to the FFT-1 method but with significant modifications. The weight stacking procedure for non-uniform SAFs can be expressed in the following way:

$$\begin{cases} W(l) = W_k^{SAF}(((l))_{Ns}) & l = [0, N/2) \\ W(l) = 0 & l = N/2 \\ W(l) = W(N-l)^* & l = (N/2, N) \end{cases}, \quad (3.10)$$

where $W(l)$ is the FFT bins of the fullband adaptive filter coefficients, $l = 0 \dots N-1$ is the FFT bin index, $W_k^{SAF}(l)$ is the FFT bins of the subband adaptive filter coefficients, N_s is the subband adaptive filter order, $((l))$ is the modula operation, $*$ is the complex conjugation operation, k is the frequency index of the subband,

which is expressed in the following way:

$$k = l \cdot \text{step}(\text{Hz}) . \quad (3.11)$$

Frequency index k corresponds to the real frequency in Hz. Based on the prior knowledge of the non-uniform subbands frequency boundaries, frequency index helps to define the subband, which contributes filter weights to the fullband filter at the specific frequency range. In the case of critical bands SAF, the mapping of the frequency index to the index of the critical band is shown in Table 3.2.

The last stage is the transformation of fullband filter weights from frequency to time domain.

$$w(n) = \text{IFFT}(W(l)) . \quad (3.12)$$

It is obvious that critical bands distribute the different numbers of weights to the fullband adaptive filter. Table 3.3 provides detailed information about the number of weights distributed by each critical band and their positions in the fullband adaptive filter.

With the aim to check the performance of non-uniform SAF, it was conducted a simple simulation experiment using a tonal 500 Hz signal as the desired signal and a tone of 500 Hz corrupted by white noise as an input signal.

Figure 3.8 shows the results and performance of the critical bands SAF. The proposed critical bands SAF and weight stacking algorithm for non-uniform delayless SAFs are workable and can be used for further tasks and applications. To conclude this subsection, it is possible to state that a new critical bands SAF and new weight stacking algorithm for non-uniform delayless SAF was proposed, developed and implemented. Weight stacking algorithm is useful for all non-uniform filter banks, but it requires the prior knowledge of the filters' order, frequency boundaries of subbands and their number. Simulation results prove the working ability of the proposed algorithms and approaches.

Table 3.2 Frequency index k

Number of the critical band	Frequency range of the index k , Hz
0	0 - 43.07
1	86.14 – 172.28
2	215.35 – 301.49
3	344.56 – 473.77
4	516.84 – 602.98
5	646.05 – 732.19
6	775.26 – 904.47
7	947.54 – 1076.75
8	1119.82 – 1249.03
9	1292.10 – 1421.31
10	1464.38 – 1636.66
11	1679.73 – 1895.08
12	1938.15 – 2153.50
13	2196.57 - 2454.99
14	2498.06 - 2799.55
15	2842.62 - 3230.25
16	3273.32 - 3704.02
17	3747.09 - 4350.07
18	4393.14 - 5168.40
19	5211.47 - 6288.22
20	6331.29 - 7838.74
21	7881.81 - 10164.52
22	10207.59 - 13696.26
23	13739.33 - 18950.80
24	18993.87 - 22008.77

3.2.3 Psychoacoustic ANC Algorithm

Critical bands SAF was applied to get a critical bands subband ANC algorithm, firstly, and to implement a new psychoacoustic subband ANC algorithm [73] after this. 25 critical bands cover the frequency range of 0-22050 Hz in the implemented critical bands SAF. However, the 25 bands system is too many for real-time ANC applications. Moreover, ANC algorithms are efficient for the frequencies below 1.5 – 2 kHz. Therefore, it was decided to investigate the most efficient frequency range of critical bands subband ANC algorithm to reduce the number of subbands.

Table 3.3 Contribution of subband weights to fullband filter

Number of the critical band	Number of the contributed coefficients to the fullband filter	Range of the contributed subband DFT bins
0	2	$W_0(0) - W_0(1)$
1	3	$W_1(2) - W_1(4)$
2	3	$W_2(5) - W_2(7)$
3	4	$W_3(8) - W_3(11)$
4	3	$W_4(12) - W_4(14)$
5	3	$W_5(15) - W_5(17)$
6	4	$W_6(18) - W_6(21)$
7	4	$W_7(22) - W_7(25)$
8	4	$W_8(26) - W_8(29)$
9	4	$W_9(30) - W_9(33)$
10	5	$W_{10}(34) - W_{10}(38)$
11	6	$W_{11}(39) - W_{11}(44)$
12	6	$W_{12}(45) - W_{12}(50)$
13	7	$W_{13}(51) - W_{13}(57)$
14	8	$W_{14}(58) - W_{14}(65)$
15	10	$W_{15}(66) - W_{15}(75)$
16	11	$W_{16}(76) - W_{16}(86)$
17	15	$W_{17}(87) - W_{17}(101)$
18	19	$W_{18}(102) - W_{18}(120)$
19	26	$W_{19}(121) - W_{19}(146)$
20	36	$W_{20}(147) - W_{20}(182)$
21	54	$W_{21}(183) - W_{21}(236)$
22	82	$W_{22}(237) - W_{22}(318)$
23	122	$W_{23}(319) - W_{23}(440)$
24	71	$W_{24}(441) - W_{24}(511)$

The critical bands subband ANC (CB ANC) algorithm is implemented using four different numbers of critical bands and, thus, for different frequency ranges. The following numbers of critical bands are used for investigation: 13 critical bands (0 - 2153.50 Hz), 18 critical bands (0 – 4350.07 Hz), 21 critical bands (0 - 7838.74 Hz) and 25 critical bands (0 – 22050 Hz). Two noise sources are used for simulation experiments to compare performances of different critical bands number ANC algorithm: broadband white noise of full working frequency range 20-22050 Hz and the sum of the 25 single tones of center frequencies of each critical band. Table 3.4 shows noise reduction results for both noise signals and different critical bands number ANC algorithm.

Figure 3.8 – a) Input signal (500 Hz tone corrupted by white noise); b) Desire signal (500 Hz tone); c) Output of critical bands SAF; d) Error signal;

Table 3.4 Simulation result of different critical bands number ANC algorithm

Noise type/ CB number	13 bands (0- 2153.50 Hz)	18 bands (0- 4350.07 Hz)	21 bands (0- 7838.74 Hz)	25 bands (0- 22050 Hz)
White Noise	-8 dB	-14.4 dB	-15 dB	-16.1 dB
Sum of Tones	-12.3 dB	-21.3 dB	-22.3 dB	-23.2 dB

A significant difference in noise reduction performance is observed between 13 CB ANC implementation and 18 CB ANC implementation. However, there is no significant improvement of performance for the CB ANC algorithm with a higher number of critical bands. Therefore, it was decided to use 18 critical bands for the proposed psychoacoustic ANC algorithm. Moreover, as was mentioned in Sub-section 2.3.1, human's hearing is the most sensitive in the frequency range till 4000 Hz. According to this fact and simulation results, the CB ANC algorithm is implemented in 18 critical bands and it operates in the frequency range till 4350.07 Hz. Figure 3.9 shows the transfer from the full critical bands filter bank

to the filter bank, which is used in this work. As was mentioned above, the subband ANC algorithm achieves a faster convergence rate because of the decimation factor, which reduces the order of subband adaptive filters.

Transfer from 25 critical bands filter bank to 18 critical bands filter bank helps to introduce higher decimation factor for subband ANC algorithm. The decimation factor is defined by the bandwidth of the widest frequency subband of the filter bank [80]. The 25th critical band has bandwidth about 8000 Hz. The maximum possible decimation factor for full 25 critical bands filter bank is expressed as follows:

$$D = \frac{f_s}{2BW} = \frac{44100}{16000} \approx 2. \quad (3.13)$$

The bandwidth of 18th critical is about 650 Hz. Therefore, the maximum decimation factor is:

$$D = \frac{f_s}{2BW} = \frac{44100}{1300} \approx 32. \quad (3.14)$$

The proposed CB ANC algorithm can be applied for real-time applications. A possibly higher decimation factor and a smaller number of critical bands save computational resources and time. Moreover, it allows for introducing additional algorithms to get better noise reduction and sound quality results.

Figure 3.9 – CB filter banks of 25 and 18 bands

The proposed psychoacoustic subband ANC algorithm has a goal to reduce only audible noise components. It is assumed that the proposed approach has the same perceptual results as conventional subband ANC algorithm and reduce computational cost and time. It is obvious that the headphones ANC algorithm operates in the presence of the target audio signal, which can mask out some noise components and makes them inaudible for the human's hearing system. The psychoacoustic analysis is useful to define the audibility of noise according to the acoustic situation. At this stage, it was used a simple psychoacoustic model [81] to estimate the masking threshold [40] of the target audio signal and to compare it with the SPL of the primary noise signal. A more complicated psychoacoustic model is used for the system, described below in this thesis. Therefore, a full and detailed description of the applied psychoacoustic model is presented in Section 4.1.1. The block diagram of the proposed psychoacoustic ANC algorithm is shown in Figure 3.10.

Primary noise at the error microphone is not directly available because it is mixed with the target audio signal and noise control signal. As was mentioned above, the integrated audio ANC algorithm subtracts the target audio from the error signal. In a similar way, it is done for the noise control signal in order to get an estimated version of the primary noise $d(n)$.

$$e''(n) = e(n) - \mathbf{a}(n) * \hat{\mathbf{s}}(n) + ((\mathbf{x}(n) * \mathbf{w}(n)) * \hat{\mathbf{s}}(n)). \quad (3.15)$$

The psychoacoustic masking model uses the same critical bands or auditory filter bank as CB ANC algorithm. However, the masking model operates in full 25 critical bands because neighboring frequency bands have an influence on the masking thresholds of each other. The masking threshold of the target audio and SPL of primary noise are compared in each critical band to define bands with audible noise components. Figure 3.11 shows an example of this comparison based on one time frame of broadband white noise as primary noise and classical Vivaldi's symphony as target audio. The noise component is inaudible if its critical band SPL is lower than the masking threshold. It is obvious from Figure 3.11 that noise components of the first 5 critical bands are inaudible in the presence of the target audio. The psychoacoustic masking model allows us to update subband filters weights only for bands with an audible noise, for other bands, weights are still the same as in the previous iteration.

Figure 3.11 – Masking threshold and noise SPL

The procedure can be expressed as follows:

$$\begin{aligned}
& \text{If } \text{Noise } \text{SPL}(m) \geq \text{Threshold}(m) \{ \\
& \quad \mathbf{w}_m(n+1) = \mathbf{w}_m(n) + \mu \frac{\mathbf{x}_m^*(n) e_m'(n)}{\|\mathbf{x}_m'(n)\|^2} \\
& \} \\
& \text{Else if } \text{Noise } \text{SPL}(m) < \text{Threshold}(m) \{ \\
& \quad \mathbf{w}_m(n+1) = \mathbf{w}_m(n) \\
& \}
\end{aligned}$$

Additional computations caused by the psychoacoustic model can increase computational burdens [82] of the psychoacoustic ANC algorithm. However, real-life noises cannot change their features and behavior very fast in time. Therefore, the ANC algorithm operates sample-by-sample but the psychoacoustic masking model recomputes masking threshold and noise SPL frame-by-frame every 0.4 seconds. Thus, the psychoacoustic ANC algorithm helps to reduce computational cost and time because it doesn't update all critical bands' weights each iteration. The perceptual quality of the target audio should be the same as for conventional subband ANC algorithm because inaudible noise components have no influence on the sound quality.

3.3 Analysis of Psychoacoustic Subband ANC Algorithm Performance

Results of the proposed psychoacoustic ANC algorithm and comparisons with conventional ANC algorithm are discussed in this section. Comparisons are made in terms of subjective psychoacoustic evaluations. Firstly, experimental conditions and systems' setups are presented. Simulation results and comparisons are discussed in the second part of this section. Results prove the efficiency of the proposed psychoacoustic subband ANC algorithm.

3.3.1 Systems for Comparison

The proposed psychoacoustic subband ANC algorithm is compared with the conventional subband ANC algorithm. Comparisons are conducted based on

simulation results implemented in Matlab [83]. Actual primary and secondary paths of real headphones, which are measured before in the anechoic chamber [84], are used in simulations. It is assumed that the noise source situated in front of the dummy head at a distance of 1.5 meters. Figure 3.12 shows the frequency responses of actual primary and secondary paths.

Both ANC algorithms apply 1024 taps order fullband adaptive filters. In order to get a fair comparison, the conventional subband ANC algorithm is also implemented using 18 critical bands (0-4350.07 Hz). Therefore, the conventional subband ANC algorithm reduces all noise components within 18 critical bands and the psychoacoustic ANC algorithm operates on the audible noise components. ANC algorithms are implemented based on an audio integrated technique to evaluate the perceptual quality of the target sound.

3.3.2 Simulation Results

Simulations are conducted to evaluate performances of both ANC algorithms in terms of noise reduction, psychoacoustic evaluations [85] and computational cost. Firstly, three noise sources are used for simulation experiments: broadband white noise (20 – 20000 Hz), engine noise and recorded traffic noise.

Figure 3.12 – a) Frequency response of primary path; b) Frequency response of secondary path

Classical music, soft and slow rock ballad and fast aggressive hard rock are used as the target audio signals. The ANC algorithms are compared using all possible mixes of noise sources and the target sounds. Therefore, there are 9 simulation scenarios. The aim of these simulations is to compare psychoacoustic subband ANC and conventional subband ANC algorithms in terms of the perceptual quality of the target sound after the noise reduction procedure. The following objective psychoacoustic evaluations are used for comparison: loudness, based on Glasberg and Moore loudness estimation model [12]; Plomp's and Levelt's roughness model [86] and sharpness estimation, proposed by Zwicker [42].

Tables 3.5, 3.6 and 3.7 show noise reduction performance and psychoacoustic evaluations for all possible noises and the target signals mixes. Psychoacoustic evaluations are also presented for the clear target audio signal and target audio + noise before the ANC algorithm applying.

It is obvious that the conventional subband ANC algorithm has better noise reduction performance. On average, the conventional subband ANC algorithm's noise reduction performance is 4-5 dB higher because it reduces all noise components till 4000 Hz. However, psychoacoustic evaluations are more important for headphones applications as they define the perceptual quality of sound. The conventional subband ANC and proposed psychoacoustic subband ANC algorithms have similar evaluations of loudness, roughness, and sharpness for all scenarios. Therefore, the proposed psychoacoustic subband ANC algorithm achieves the same perceptual quality as the conventional ANC algorithm. Moreover, a comparison between clear audio signal and signal after both ANC algorithms shows that roughness and sharpness are similar, without significant differences, and loudness differences do not exceed 2 sones. In [87], it was shown that loudness noticeable different is about 2 sones.

Table 3.5 Noise attenuation and psychoacoustic evaluations for white noise [73]

White noise		Audio	Audio+Noise	Conv. ANC	Psych. ANC
Classical music	Atten. (dB)	-	-	-15.1	-10.9
	Loud. (sones)	15.02	20.03	16.21	16.20
	Rough. (asper)	8.04	35.78	8.90	8.88
	Sharp. (acum)	1.21	2.65	1.34	1.32
Rock ballad	Atten. (dB)	-	-	-14.4	-10.7
	Loud. (sones)	15.66	19.53	16.03	16.02
	Rough. (asper)	8.61	36.11	9.92	9.92
	Sharp. (acum)	1.27	2.78	1.48	1.43
Hard rock	Atten. (dB)	-	-	-14.2	-10
	Loud. (sones)	17.91	21.72	18.39	18.39
	Rough. (asper)	9.03	36.89	9.50	9.51
	Sharp. (acum)	1.29	2.72	1.51	1.50

The conventional subband ANC algorithm has the same computational time and cost for all iterations. However, the computational cost of the psychoacoustic ANC algorithm depends on the number of subbands with audible noise components in each iteration. Therefore, simulation experiments are conducted in order to compare the computational time of both ANC algorithms for a different amount of audible noise components. Broadband white noise (20 – 20000 Hz) of 10 seconds duration is used in this experiment.

Table 3.6 Noise attenuation and psychoacoustic evaluations for engine noise [73]

Engine noise		Audio	Audio+Noise	Conv. ANC	Psych. ANC
Classical music	Atten. (dB)	-	-	-16.3	-11.1
	Loud. (sones)	15.02	18.91	15.23	15.21
	Rough. (asper)	8.04	18.73	8.75	8.74
	Sharp. (acum)	1.21	2.32	1.41	1.40
Rock ballad	Atten. (dB)	-	-	-15.9	-11
	Loud. (sones)	15.66	19.68	16.05	16.04
	Rough. (asper)	8.61	20.20	9.41	9.41
	Sharp. (acum)	1.27	2.56	1.42	1.41
Hard rock	Atten. (dB)	-	-	-16.2	-11.2
	Loud. (sones)	17.91	20.54	18.31	18.31
	Rough. (asper)	9.03	22.53	9.88	9.86
	Sharp. (acum)	1.29	2.71	1.50	1.50

Three different quantities of audible noise components are used: less than half of critical bands have audible noise components in each iteration, half of the critical bands have audible noise components in each iteration and more than half of bands with audible noise components in each iteration. Table 3.8 shows simulations computational time for all three cases and the computational time of the conventional ANC algorithm.

Table 3.7 Noise attenuation and psychoacoustic evaluations for traffic noise [73]

Traffic noise		Audio	Audio+Noise	Conv. ANC	Psych. ANC
Classical music	Atten. (dB)	-	-	-14.7	-10.1
	Loud. (sones)	15.02	18.32	15.87	15.86
	Rough. (asper)	8.04	23.67	8.67	8.67
	Sharp. (acum)	1.21	2.24	1.38	1.38
Rock ballad	Atten. (dB)	-	-	-13.3	-10.1
	Loud. (sones)	15.66	18.74	16.17	16.16
	Rough. (asper)	8.61	21.83	9.20	9.19
	Sharp. (acum)	1.27	2.69	1.39	1.38
Hard rock	Atten. (dB)	-	-	-14.3	-10.2
	Loud. (sones)	17.91	20.13	18.45	18.42
	Rough. (asper)	9.03	24.31	9.96	9.97
	Sharp. (acum)	1.29	2.70	1.44	1.44

Table 3.8 Computational time estimation [73]

Scenario	Conv. ANC	< half audible	≈ half audible	> half audible
Comp. time, sec	193	164	180	202

The proposed psychoacoustic ANC algorithm has higher computational time only for the case when more than half critical bands have audible noise components. It is well-known that real-life noises are not very broad. Thus, the number of critical bands with audible noise components should not be high. The

real-life scenario experiment is conducted to investigate the amount of audible noise. Recorded traffic noise acts as a primary noise signal and music signal of 4 mins and 38 secs duration acts as target audio. The psychoacoustic model operates frame-by-frame each 0.4 seconds. Table 3.9 shows the lowest number of critical bands with audible noise per frame, the highest number of critical bands with audible noise and the average number of critical bands with audible noise within the whole signal.

There is a frame with only 2 critical bands, which have audible noise in the presence of the target audio. The highest number of critical bands with audible noise is 15. However, the most significant is to define the average number of critical bands with an audible noise, which is 6 or about 33%. Therefore, it is possible to state that real-life noise scenarios have less than half of critical bands with an audible noise, which implies that the proposed psychoacoustic subband ANC algorithm achieves the same perceptual quality of sound and requires less computational resources and time compare to conventional subband ANC algorithm.

Table 3.9 Amount of audible noise components

Quantity types	Min. Number	Max. Number	Avr. Number
Critical bands num.	2	15	6
Percentage	11.1%	83.3%	33.3%

3.4 Conclusions

In this chapter, a new psychoacoustic subband ANC algorithm was proposed. The psychoacoustic subband ANC algorithm is based on the critical bands non-uniform SAF. The first contribution of this chapter is the development and implementation of the weight stacking algorithm for non-uniform SAF. The psychoacoustic subband ANC algorithm is developed based on the idea of integration the CB subband ANC algorithm with the psychoacoustic model to define and reduce only audible noise components. The proposed psychoacoustic subband ANC algorithm achieves similar listening experience with an average decreasing of the processed subbands by 67% compared to the conventional subband ANC approach.

Chapter 4

Integrated Psychoacoustic Subband ANC and Masking System

This chapter proposes a new integrated psychoacoustic subband ANC and masking system for headphones applications. As was mentioned in Chapter 2, the ANC algorithm is efficient for the low-frequency noise, below 1000 – 1500 Hz. Therefore, this chapter is based on the idea to solve the high-frequency noise reduction issue. The psychoacoustic model from the previous chapter is utilized to implement a masking algorithm to mask out high-frequency noise components. This chapter is divided into 3 sections. The first section shows the idea and working principles of the proposed integrated system. The second section presents results and comparisons of the proposed approach with noise reduction techniques from the previous studies. The proposed system outperforms other noise reduction approaches in terms of objective and subjective evaluations. The third section concludes and summarized this chapter.

4.1 ANC and Masking Integration

This section begins with the description of the psychoacoustic model and a detailed explanation of the masking threshold estimation. The first part leads to the sub-section on a detailed description of the automatic gain control block to compute the gain coefficient of the music/speech for the masking purposes. Finally, the idea of the ANC algorithm and masking integration is presented and explained.

4.1.1 Psychoacoustic Model for Integrated System

As was mentioned above, there are several psychoacoustic models [81]. Psychoacoustic models approximate the human's hearing system according to different needs. Psychoacousticians [88] implement very complex and full models with a large number of properties. These psychoacoustic models are useful for accurate spectral masking estimations. Therefore, such models also called models of "cause" [89]. On the other hand, audio engineers use human's hearing performance as a reference to model hearing limitations. Their psychoacoustic models are simpler. All effects of the human's hearing system are estimated within the psychoacoustic models. Thus, these models are called psychoacoustic models of "effect" [89]. However, most of the existing models are placed in between these two points of view. Psychoacousticians simplify complex systems by the signal processing-based model. As an example, psychoacoustic models estimate the responses of the large groups of ear's hair cells together, instead of model responses of each hair cell independently. Audio engineers also sometimes need to extend the simple psychoacoustic models and investigate the hearing system more closely and to get more accurate estimations of effects. Therefore, there are two different but parallel ways of psychoacoustic models creating: model the cause or process that gives rise to some effect or to model the effect directly. The most useful and accurate psychoacoustic model was proposed by J. Johnston [90]. Johnston's psychoacoustic model calculates the masking threshold of the audio signal to predict the audibility of signal components. This model is widely used in audio coders, where the definition of the components' audibility is used for the compression stage and to feed a bit allocation algorithm. Figure 4.1 shows a simplified block diagram of the MPEG/Audio coder. Johnston's model estimates spectral masking of observed sounds. Therefore, this psychoacoustic model is selected to satisfy the needs of this work.

Figure 4.1 – MPEG/Audio coder block diagram

Psychoacoustic masking is applied as the second stage of noise reduction algorithms, which operates after the ANC algorithm [91]. As was mentioned in Chapter 2, the integrated ANC and masking system was implemented in the previous study. Pre-recorded audio signals were used as maskers. The system defines and selects the most suitable masker according to noise situation. Such an algorithm does not fit headphones applications because users select audio tracks according to their priorities and these audio tracks should act as maskers. Also, there are approaches [92]-[93] where psychoacoustic masking was used as a single noise reduction approach, based on perceptual equalizer [94]. However, a single masking approach can be damaging to the human's hearing system because of the possibility of a high amplification level of the target audio. The two-stage approach, proposed in this work, helps to achieve better sound perceptual quality [95] and reduce most of the noise components without introducing any distortions in the target audio signal because both parts of the system are psychoacoustically motivated. Moreover, psychoacoustic masking is the second stage and its goal is to mask out residual and high-frequency noise components after ANC processing, which implies that amplification levels cannot be high. In the previous chapter, it was shown that the proposed psychoacoustic subband ANC algorithm helps to save computational resources of the ANC system, which allows introducing additional noise reduction stages. Therefore, the psychoacoustic masking algorithm is added to the psychoacoustic subband ANC algorithm to get better noise reduction performance and quality of the target sound. The psychoacoustic subband ANC algorithm uses its psychoacoustic model for the masking algorithm. Thus, the common psychoacoustic model prevents the introduction of additional computational burdens. In the proposed integrated psychoacoustic ANC and

masking system [91], the psychoacoustic model has two tasks: to control subband adaptive filters weights updating and to estimate gains coefficients for masking procedure. Figure 4.2 shows the diagram of the integrated psychoacoustic subband ANC and masking system. The psychoacoustic model has three inputs: estimated primary noise signal (3.15); primary audio signal at the error microphone

$$a'(n) = \mathbf{a}(n) * \hat{\mathbf{s}}(n); \quad (4.1)$$

and error signal without audio (residual noise)

$$e'(n) = e(n) - a'(n), \quad (4.2)$$

where $\mathbf{a}(n)$ is the target audio signal and $e(n)$ is the signal captured by error microphone.

The target audio signal is used as a masker and residual noise – as a maskee. As for the psychoacoustic subband ANC algorithm, Johnston's model operates every 0.4 seconds on 1024 length frames to recompute masking threshold and gains for the masking algorithm.

Figure 4.2 – Integrated psychoacoustic subband ANC and masking system [91]

Firstly, a frame of the target audio signal using FFT-transform. Next, the real and imaginary parts of FFT-signal are used to obtain the power spectrum.

$$P(k) = A_{\text{Re}}^2(k) + A_{\text{Im}}^2(k), \quad (4.3)$$

where $A_{\text{Re}}(k)$ and $A_{\text{Im}}(k)$ are real and imaginary parts of the target audio and k is the FFT-bin index.

As was mentioned above, the psychoacoustic model operates in critical bands. Therefore, it is necessary to calculate the energy for each critical band.

$$B(v) = \sum_{k=bl_v}^{bh_v} P(k), \quad (4.4)$$

where v is the number of the critical band, bh_v and bl_v are the highest and the lowest boundary of the critical band.

The masking threshold of a specific critical band has an influence on neighboring bands. Thus, a specific critical band masking threshold cannot be estimated independently. There are several spreading functions [96], which are used to calculate the effects of critical bands masking threshold on each other. Schroder's spreading function [97] is used in this work. The spreading function is expressed by the following equations:

$$S_{i,j}(dB) = 15.81 + 7.5(i - j + 0.474) - 17.5\sqrt{1 + (i - j + 0.474)^2}, \quad (4.5)$$

$$S_{i,j} = 10^{\left(\frac{S_{i,j}(dB)}{10}\right)}, \quad (4.6)$$

where i is the critical band of masked signal and j is the critical band of masker signal.

The spreading of critical bands energy C is estimated by convolution. It can be expressed by matrix multiplication.

$$\begin{bmatrix} C(1) \\ C(2) \\ C(3) \\ \dots \\ C(25) \end{bmatrix} = \begin{bmatrix} S_{1,1} & S_{1,2} & S_{1,3} & \dots & S_{1,25} \\ S_{2,2} & S_{2,1} & S_{2,3} & \dots & S_{2,25} \\ S_{3,1} & S_{3,2} & S_{3,3} & \dots & S_{3,25} \\ \dots & \dots & \dots & \dots & \dots \\ S_{25,1} & S_{25,2} & S_{25,3} & \dots & S_{25,25} \end{bmatrix} \begin{bmatrix} B(1) \\ B(2) \\ B(3) \\ \dots \\ B(25) \end{bmatrix}. \quad (4.7)$$

The next stage is the calculation of the tonality coefficient. As was mentioned above, masker can be noise-like and tone-like. These two masker types have different masking properties. Therefore, the masker type definition is necessary. Spectral Flatness Measurements (SFM) approach [98] is used to define the signal type. SFM requires geometric and arithmetic means of power spectrums.

$$\log_{10}(GM) = \frac{1}{N} \sum_{n=1}^N \log_{10}(P(n)), \quad (4.8)$$

$$\log_{10}(AM) = \log_{10} \left[\frac{1}{N} \sum_{n=1}^N P(n) \right], \quad (4.9)$$

where N is the half of frame size.

$$SFM(dB) = 10 \log_{10} \left(\frac{GM}{AM} \right). \quad (4.10)$$

Tonality coefficient [99] is expressed by the following equation:

$$\alpha = \min \left(\frac{SFM(dB)}{SFM_{\max}}, 1 \right), \quad (4.11)$$

where $SFM_{\max} = -60$ dB.

The threshold offset is determined as follows:

$$O(v) = \alpha(14.5 + v) + (1 - \alpha)5.5. \quad (4.12)$$

Therefore, if the tonality coefficient equals 1 masker is defined as tone-like, otherwise, noise-like.

The estimated masking threshold is calculated by subtraction of the offset from the spreading critical bands' energy.

$$T(v) = 10^{\log_{10}(C(v)) - (O(v)/10)}. \quad (4.13)$$

In general, the spreading function increases the energy of masker, however, the aim is to model energy spreading by dispersing it. Therefore, the normalization of the masking threshold is applied to simulate the spreading effect. Firstly, the spreading threshold error is calculated.

$$\begin{bmatrix} C_E(1) \\ C_E(2) \\ C_E(3) \\ \dots \\ C_E(25) \end{bmatrix} = \begin{bmatrix} S_{1,1} & S_{1,2} & S_{1,3} & \dots & S_{1,25} \\ S_{2,2} & S_{2,1} & S_{2,3} & \dots & S_{2,25} \\ S_{3,1} & S_{3,2} & S_{3,3} & \dots & S_{3,25} \\ \dots & \dots & \dots & \dots & \dots \\ S_{25,1} & S_{25,2} & S_{25,3} & \dots & S_{25,25} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ \dots \\ 1 \end{bmatrix}. \quad (4.14)$$

Finally, the normalized threshold is estimated by subtraction of spread error threshold from the estimated masking threshold.

$$T'(v) = T(v) - 10 \log_{10}[C_E(v)]. \quad (4.15)$$

The next step is a conversion to the real dB SPL scale to take into account ATH. In [100], it was shown that 105 dB SPL at a distance of 1 m is an average maximum level of listening at home. Generally, the 90 dB SPL is suggested as a reference value for conversion. To convert the masking threshold to the real dB SPL scale, a 1 kHz sine tone is used as a reference. The difference between the power of the reference tone and maximum level of 90 dB SPL is added to the normalized masking threshold to get a real dB SPL values:

$$T'_{spl}(v) = T'(v) + (90 \text{ dB} - P_{ref}), \quad (4.16)$$

where P_{ref} is the SPL of the reference.

It is necessary to compare the raw masking threshold with the absolute threshold of hearing (ATH) (2.9) for each critical band. In Johnston's model, the median of each band ATH is taken for comparison with the raw threshold. This approach can define the sound is masked when it is audible. Thus, it was decided to use the minimum value of each critical band ATH. In this case, sound can be defined as audible when it is masked. However, it is more useful for the proposed noise reduction system. The final equation of the masking threshold is a definition of maximum value between the raw threshold and ATH:

$$T''(v) = \max[T'_{spl}(v), ATH(v)]. \quad (4.17)$$

The masking threshold plays an important role in the proposed integrated noise reduction system. Firstly, as was mentioned in Chapter 3, primary noise components are not processed by the ANC algorithm, if they are situated below the masking threshold of the target audio. Another important feature, it is to define the audibility of residual, after ANC, noise. Residual noise components, situated above the masking threshold, should be masked out by the amplification of the target audio, which makes masking threshold higher than residual noise SPL in the requiring critical bands. Finally, the masking threshold helps to estimate gain coefficients of the target audio to mask out audible components of residual noise.

4.1.2 Automatic Gain Control (AGC) algorithm

From Figure 4.2, the psychoacoustic model provides information about the current masking threshold and SPL of residual noise to the AGC block. AGC block is based on the idea of perceptual equalizer [94], with the aim to estimate gain coefficients for the target audio to mask out residual noise. AGC block compares the masking threshold and SPL of the residual noise for each critical band. In the case, if residual noise has SPL higher than the masking threshold in the specific critical band, AGC calculates the gain coefficients for the target audio. Figure 4.3 shows the masking threshold and residual noise SPL on the example of the one frame. Broadband noise acts as a primary noise and popular classic rock song acts as target audio. Chapter 2 mentioned that the psychoacoustic subband ANC algorithm operates in 18 critical bands, where it is the most efficient and human's hearing system is the most sensitive. As a result, audible noise components are presented only in the high-frequency critical bands. Therefore, the target audio needs to be amplified only in a few numbers of bands, which should not introduce significant distortions. Gain estimation process can be expressed in the following way. Firstly, AGC computes the difference between the masking threshold and residual noise SPL for each critical band:

$$dif(v) = Rn(v) - T''(v), \quad (4.18)$$

where $Rn(v)$ is the SPL of residual noise.

Non-negative values of difference (4.18) imply that residual noise is still audible in the specific critical band.

Figure 4.3 – Masking threshold and SPL of residual noise [91]

In a previous study [46], it was shown that for most of the critical bands, if the masking threshold is on average 2 dB higher than the SPL of maskee for noise-like maskers, it can guarantee that maskee is completely inaudible. Thus, the values of the gain coefficients are estimated as follows:

$$g(v) = dif(v) + 2, \quad (4.19)$$

where $dif(v)$ is a difference between maskee and masking threshold levels in dB, v is a critical band's index.

Finally, dB gain coefficients are converted in intensity values for applying on the audio signal in the time domain.

AGC estimates gain coefficients for each critical band independently. Moreover, gain coefficients are recomputed each frame. Therefore, there is a high possibility to face a problem of a level-changeable sound in both frequency and time domains. It is necessary to implement gain averaging procedure to prevent pumping sound effect. Figure 4.4 shows the block diagram of the AGC block. Gain averaging procedure consist of two independent stages, one is for

frequency domain and another one is for the time domain.

The time-domain averaging procedure is based on the averaging table approach [101]. The averaging table collects the gain coefficients for all critical bands from the previous frames and estimated the gain coefficients for the current frame based on the previous frames' gains. The example of the averaging table is shown in Figure 4.5. The size of the averaging table N_{at} (number of the previous frames) can be adjusted. The longer average table order makes amplification smoother but the algorithm becomes slower. In other words, the order of the average table is a trade-off between the adaptation speed and the sound quality of the target audio signal. Informal listening tests in the previous study [102] showed that the averaging time can be quite long (more than 10 seconds), because human hearing adapts rather slowly, and it is insensitive to short noise bursts, especially in the presence of musical content. However, the slow adaptation speed becomes an issue when the noise ends abruptly.

Figure 4.4 – Block diagram of the AGC

		Frame Number			
Critical Band	$g(1,1)$	$g(1,2)$	$g(1,3)$	...	$g(1,N_{at})$
	$g(2,1)$	$g(2,2)$	$g(2,3)$	...	$g(2,N_{at})$
	$g(3,1)$	$g(3,2)$	$g(3,3)$	...	$g(3,N_{at})$
	$g(4,1)$	$g(4,2)$	$g(4,3)$	...	$g(4,N_{at})$
	...	...	...	...	...
	$g(25,1)$	$g(25,2)$	$g(23,3)$	...	$g(25,N_{at})$

Figure 4.5 – An example of an averaging table

The major milestone is to define and choose the right order of the averaging table. The trade-off is between the smooth sound (high order) and computational loads (low order). Moreover, in our case, it is necessary to note that the high order averaging table can decrease masking performance because the audible noise components may vary from frame to frame. The psychoacoustic masking algorithm of a full integrated system operates in 25 critical bands, which implies that we have a vector of the gain coefficients, which consists of the 25 gains corresponding to each critical band. With the aim to define the order of the averaging table, it was decided to compare different orders in terms of the maximum loudness difference between neighboring frames and masking performance. Masking performance is evaluated by subjective tests. It was proposed to evaluate how good the target audio masks out residual background noise to participants. The evaluation scale consists of 5 points. Table 4.1 shows the masking performance evaluation scale.

The comparisons are made for the two noise sources of broadband noise (20 – 20000 Hz) and recorded traffic noise (up to 8000 Hz); and classical music (Vivaldi's symphony), which acts as target audio. Tables 4.2 and 4.3 show comparison results between 5 different orders of averaging tables for both noise sources. It is known that loudness noticeable difference is about 2 - 2.5 sones

[103]. According to the comparison results, the most preferable order of the averaging table is 4. The order of 4 provides a satisfying trade of between the masking quality and the loudness difference. The aim is to get the masking quality around 4 and to get the loudness difference no noticeable or hard noticeable. The order of 4 frames satisfies masking requirements and the maximum loudness difference between neighboring frames is also not so high. Finally, the averaging table of the size 25x4 is used for gains averaging in the time domain.

Table 4.1 Masking performance evaluation scale

Evaluation scores	Description of scores
1	Masking does not perform well. Noise is still dominant.
2	Masking does not perform well. Noise and target audio are audible at similar levels.
3	Masking has average performance. Target audio is dominant, but noise is still audible
4	Masking performs well. Only a few of noise components are audible
5	Masking performs excellent. Noise is inaudible.

Table 4.2 Averaging table orders comparison results for traffic noise

Order/Evaluation type	No averaging	2 frames	4 frames	6 frames	8 frames
Loudness dif., sones	6.18	2.94	2.10	2.01	1.85
Masking score	4.36	4.12	4.03	3.94	3.07

Table 4.3 Averaging table orders comparison results for broadband noise

Order/Evaluation type	No averaging	2 frames	4 frames	6 frames	8 frames
Loudness dif., sones	8.53	3.63	3.17	2.73	2.15
Masking score	4.30	4.02	3.88	3.27	2.86

Gains averaging procedure in the frequency domain differs from the time-domain procedure. The highest gains' values are for the high-frequency bands, because, as was mentioned above, the ANC algorithm operates only till 4000 Hz. Therefore, it is necessary to achieve good masking performance at the high-frequency range, which implies gain averaging procedure should be implemented according to the highest gain coefficient's value. The frequency-domain gain averaging is possible to describe in the following way. The highest value gain coefficient is found. The next step is to take into account two neighboring gain coefficients of the previous and the next critical band. The average value of these three coefficients defines the gain coefficient for the central critical band. To define gain coefficients' values for all critical bands, we move from the current highest gain value critical band in both directions, to the first and the last critical band and calculate gain values in the same way, as an average value between three neighboring critical bands. The proposed approach showed efficient performance in terms of the loudness difference between critical bands' components and masking performance is still high.

The gain coefficients vector is the output of the AGC block. The FFT is applied to the target audio in order to multiply critical bands' audio components by the corresponding gain coefficient, then IFFT applied to the amplified audio. FFT-IFFT loop operates on short frames and the Hamming window was used. The length of the frame is the same as the length of the FFT transformation. Band-wise amplification is being carried out, just like in the design of hearing aids [104], which prevents different amplification for neighboring frequency bins and distortion in the reconstructed signal. Furthermore, the gain is adjusted based on the signal's power just to mask out the residual noise. Therefore, amplification in the frequency-domain has not significant perceptual influence on the quality of the audio signal and it cannot cause any temporal or frequency aliasing issues. In fact, the estimated audio signal at the error microphone is possible to express by the following equation:

$$a'(n) = [\mathbf{a}(n)\mathbf{g}(n)] * \hat{\mathbf{s}}(n), \quad (4.20)$$

where $\mathbf{a}(n)$ is the vector of the audio signal and $\mathbf{g}(n)$ is the gain coefficients vector.

It is important to note that psychoacoustic masking has an influence on the psychoacoustic ANC algorithm. The amplified audio signal has better masking ability and more primary noise components are inaudible in the presence of the amplified the target audio, which implies that less number of subband filters should be updated. However, it is not possible to state that usage of masking helps to achieve less number of subband filters to update by psychoacoustic ANC algorithm all time, it depends on the type of the noise source and target audio signal. Nevertheless, experimental results show that after masking and audio amplification, the number of subband filters, which are necessary to update, is less on average 2–3 filters. Therefore, integrated psychoacoustic masking is applied to mask out residual and high-frequency noise and at the same time, it also helps to mask out some components of primary noise and decrease psychoacoustic ANC algorithm computational loads. The proposed integrated psychoacoustic ANC and masking system has a strong connection between two processing parts. Psychoacoustic ANC noise reduction influence on the type and level of residual noise, which predetermines psychoacoustic masking work, and amplification of the target audio signal, caused by masking, can mask out components of the primary noise at the next iteration and have the influence on psychoacoustic ANC part.

4.1.3 Musical Genres and Noise Types Patterns

This section is based on the idea to create different pre-setups for integrated psychoacoustic subband ANC and masking system. Humans usually have different musical preferences. Music genres [105] are defined by different frequency contents and different dominant frequency bands. Moreover, environmental noise sources are also quite different in terms of frequency content. This observation leads to the idea to simplify the psychoacoustic subband ANC algorithm based on the properties of different musical genres and noise types. Psychoacoustic ANC algorithm operates in 18 critical bands and it

defines the audibility of noise in each critical band by default. However, different frequency contents of music genres lead to the different masking properties of the target audio and it is not necessary to use all 18 critical bands and check the audibility of the noise in each band. It can be enough just to choose the pre-setup mode for a specific genre and the psychoacoustic ANC algorithm will operate only in the bands according to pre-set up mode without checking the noise audibility. The same pre-setup modes also can be introduced based on the noise type. It can help to reduce the computational loads and make the psychoacoustic ANC algorithm simpler.

To define music-based pre-setup modes, seven of the most popular musical genres (soft rock, classical music, blues/jazz, hard rock, pop music, club music, hip-hop) [106] are analyzed to define the dominant frequency bands and the average masking threshold of each genre. Three tracks of each genre are used for further analysis. Firstly, the masking thresholds of all 21 tracks are estimated. The estimations show that masking thresholds of the same musical genres are quite similar. Hard rock tracks (black line) have the highest masking threshold, especially in the 11 – 20 critical bands. Blues/Jazz (magenta line) tracks have the worst masking properties. The biggest fluctuation between tracks of one genre is possible to observe for classical music (green line). Figure 4.6 shows the masking thresholds based on musical genres. Average masking thresholds are easier to investigate and define the masking properties of different musical genres. Hard rock music has the best masking properties. Especially, it has a much higher threshold in the bands from 8 till 18 in comparison with other genres. Hard rock music consists of long-time and high-amplitude guitar parties [107] in the mid- and high-frequency ranges. Club music has better masking properties in the low-frequency range (1-4 critical bands), it can be explained by the big amount of bass sound [108]. However, blues/jazz and classical music have the worst masking properties. These musical genres are defined by smooth, low amplitude sounds with the limited frequency range.

To complete the definition of music-based [109] pre-setup modes, it is necessary to estimate SPL of the different noise types. Moreover, SPL of different noise types is necessary for noise-based [110] pre-setup modes definition. Four noise sources are used for estimations: broadband white noise,

engine noise, recorded MRT (metro/underground) noise and recorded traffic noise. Figure 4.7 shows the SPL of different noise sources. Engine noise is dominant in the low-frequency critical bands. Broadband noise has quite flat SPLs for most of the critical bands. To finalize music-based pre-setup modes, masking thresholds of different musical genres are compared with noise SPL. Obviously, it is difficult to define music-based modes for different noise types with different SPLs, because of some regularities, which can be applied for one noise type and cannot be used for others. Therefore, it was decided to use average SPL of noise types and compare it with masking thresholds of different musical genres for music-based modes. Figure 4.8 shows the masking thresholds of different musical genres and an average SPL of four noise types.

Figure 4.6 – Average masking threshold of different musical genres, soft rock, classical music, blues/Jazz, hard rock, pop music, club music, rap/hip-hop

From Figure 4.8, it is possible to assume that the ANC algorithm in hard-rock mode can operate in the smallest number of the critical bands, soft rock also has good masking properties, classical music and blues/jazz ANC modes should operate in the most number of the critical bands. Pop, hip-hop and club music is possible to join in one pre-setup mode.

Figure 4.7 – SPL of different noise types, broadband white noise (blue), engine noise (red) traffic noise (green) and MRT noise (black)

Figure 4.8 – Masking thresholds of different musical genres, soft rock (red line), classical music (green line), Blues/Jazz (magenta line), hard rock (black line), pop music (blue line), club music (light blue), Rap/Hip-Hop (yellow line) and average noise SPL

The same procedure is conducted for the noise-based modes. Four noise types SPLs are compared with the average masking threshold of seven musical

genres. Figure 4.9 shows this comparison. Traffic and MRT noises are mostly masked in the high-frequency critical bands. Broadband white noise is the most difficult type of noise for masking.

Pre-setup modes for the psychoacoustic ANC algorithm are based on the idea that the ANC algorithm operates only in the critical bands, which are defined by the mode. Music-based modes turn on the ANC algorithm only for the bands, where the masking threshold of a specific genre is situated below the average SPL of different noise types. Noise-based modes work in the opposite way, the ANC algorithm operates only in the bands where the average masking threshold is situated below the SPL of the specific noise type. Table 4.4 presents all possible pre-setup modes with the number of critical bands where the ANC algorithm works. As a result, 9 pre-setup ANC modes are introduced. One is the default psychoacoustic ANC algorithm with noise audibility definition, 5 music-based modes, and 3 noise-based modes.

Figure 4.9 – SPL of different noise types, broadband white noise (blue), engine noise (red) traffic noise (green) and MRT noise (black) and average masking threshold of 7 musical genres

Table 4.4 Pre-setup ANC modes

Mode number	Signal type	Operating critical bands	Noise audibility definition
0	default	1-18	Yes

1	Hard rock (music based)	2-10	No
2	Soft rock (music based)	2-13	No
3	Blues/Jazz (music based)	2-17	No
4	Classical (music based)	2-18	No
5	Hip-hop/Pop/Club (music based)	2-10; 16-18	No
6	White noise (noise based)	3-18	No
7	Engine noise (noise based)	2-10; 16-18	No
8	MRT/traffic noise (noise based)	2-10	No

However, it is not possible to state that all modes will be all time-efficient because these modes depend not only on the genres and noise types but also on the amplitude levels of the target audio and environmental noise. It is possible to assume such a scenario that even if a user selects one of the modes, he can be not satisfied by the noise reduction performance because of the very high-amplitude environmental noise. In such situations, the best solution is to use default psychoacoustic ANC mode with the definition of the noise audibility in each critical band.

It is necessary to note that, currently, it is the only primary stage of this study and it is not fully completed. To complete this study, it is necessary to investigate a larger database. More audio tracks and noise samples can guarantee a more accurate estimation of masking thresholds and SPL of noise types.

4.2 Analysis of Psychoacoustic Subband ANC and Masking System

This section presents objective and subjective results and comparisons of the proposed integrated system with other noise reduction approaches. Firstly, relevant noise reduction approaches for comparison are described. Comparisons are conducted in terms of objective and subjective psychoacoustic evaluations. Results show the advantages of the proposed integrated system in comparison with other noise reduction approaches.

4.2.1 Approaches for Comparison

The proposed integrated psychoacoustic ANC and masking system is

compared with four others noise reduction approaches:

- conventional integrated audio subband ANC algorithm (*Conv. ANC*), described in Section 3.1.2;
- psychoacoustic ANC algorithm (*Psych. ANC*) without masking, proposed in Chapter 3;
- masking algorithm (*Masking*) from perceptual equalizer paper [94];
- A-weighting psychoacoustic ANC algorithm (*A-weight. ANC*) [111].

The masking algorithm for perceptual equalizer is passed on pure psychoacoustic masking procedure without additional noise reduction algorithms. In [94], the psychoacoustic model is applied to estimate the masking threshold of the environmental noise and calculate the gain coefficient for the target audio to make it audible in the presence of the noise. However, for a fair comparison, this approach is modified to estimate the masking threshold of the target audio and calculates gains to mask out environmental noise. Figure 4.10 shows the idea of the perceptual equalizer masking approach.

In [111], the psychoacoustic subband ANC algorithm is based on the additional A-weighting [112] procedure. The idea is to add an A-weighting filter to process adaptive filter input and error signal. Figure 4.11 shows the block diagram of the psychoacoustic subband ANC algorithm based on A-weighting.

A-weighting matches with human's hearing system. Therefore, A-weighting is useful to get noise reduction corresponding to the human's hearing. A-weighting is calculated in the following way:

$$R(f) = \frac{12200^2 f^4}{(f^2 + 20.6^2)(f^2 + 12200^2)\sqrt{(f^2 + 107.7^2)(f^2 + 737.9^2)}}. \quad (4.21)$$

Noise reduction results show that A-weighting ANC algorithm helps to decrease the loudness of residual noise compared to the conventional subband ANC algorithm.

Figure 4.10 – Masking algorithm for perceptual equalizer

Figure 4.11 – Psychoacoustic subband ANC algorithm based on A-weighting filtering, $\mathbf{h}(n)$ is the impulse response of A-weighting filter

The experimental setups are similar to the setup from Section 3.3.1. All ANC algorithms operate in 18 critical bands. The order of fullband filter is 1024 taps and the subband filter's order is 32 taps.

4.2.2 Objective Evaluations

It is assumed that the proposed psychoacoustic subband ANC and masking system should achieve a better perceptual quality of the target audio and reduce or make inaudible the most of the environmental noise components. Thus, comparisons are made in the psychoacoustic terms. Firstly, objective psychoacoustic evaluations [85] are conducted in terms of loudness, roughness, and sharpness. Simulation experiments are made in Matlab. Loudness is estimated using the Glasberg and Moore model [12], and Plomp and Levelt's model [86] is used for roughness estimation. The last objective psychoacoustic evaluation term – sharpness, it is estimated using Zwicker and Fastl's model [42]. Different types of real-life and synthetic primary noises and different target audio signals are used in this experiment. However, it is obvious that for fair and accurate comparisons in order to show all the advantages and disadvantages of ANC and masking algorithms, it is necessary to choose the most suitable signals. The noise signal consists of two components. The first component is the broadband noise of the frequency range 3500–22000 Hz. The second component is the tonal noise of 400 Hz frequency. Noise signals are chosen according to the idea to show the efficiency of both ANC and masking algorithms. Tonal noise is low-frequency, should be reduced by the ANC algorithm. Broadband white noise has a high-frequency range in order to check the efficiency of the masking procedure. A music signal with broadband range is used as a target audio signal. Hard rock track is used because, as was shown above, this genre has the best masking properties. It is necessary to note that simulation experiments and subjective/objective perceptual evaluations were made for three different SNR scenarios: 0 dB, -5dB, -10 dB, which implies ratio between the primary noise and target audio signal before any processing. The results for three SNR levels are presented in Tables 4.5 – 4.7. Where *Original* is the primary noise and target audio without any noise reduction processing, *Psych. ANC* is a psychoacoustic ANC algorithm, *Conv. ANC* is a conventional integrated audio subband ANC algorithm, *Masking* is the masking algorithm of the perceptual equalizer, *A-weight. ANC* is a psychoacoustic ANC algorithm based on A-weighting and *ANC + Masking* is our proposed algorithm.

Loudness is a standardized psychoacoustic evaluation. A loudness of 1 sone is equivalent to the sound of 1 kHz tone at 40 dB SPL. Roughness and sharpness

have not any defined standards and their evaluations depend on the using model. The unit of sharpness is acum. A narrow-band noise at 1 kHz with a bandwidth smaller than 150 Hz and 60 dB SPL has a roughness of 1 acum. The unit of roughness is asper. One asper is defined as the roughness produced by a 1 kHz tone of 60dB SPL which is 100% amplitude modulated at 70 Hz. However, it is necessary to observe the noticeable differences in objective psychoacoustic evaluations before starting to analyze results.

Table 4.5 Objective psychoacoustic evaluations for 0 dB SNR

Scenario/Evaluation type	Loudness, sones	Sharpness, acum	Roughness, asper
<i>Original</i>	20.28	1.65	34.38
<i>Psych. ANC</i>	18.33	1.23	28.25
<i>Conv. ANC</i>	18.42	1.23	28.86
<i>Masking</i>	27.31	1.70	75.89
<i>A-weight. ANC</i>	18.33	1.21	27.04
<i>ANC+Masking</i>	19.68	1.15	29.23

Table 4.6 Objective psychoacoustic evaluations for -5 dB SNR

Scenario/Evaluation type	Loudness, sones	Sharpness, acum	Roughness, asper
<i>Original</i>	21.59	1.74	41.64
<i>Psych. ANC</i>	18.58	1.32	31.33
<i>Conv. ANC</i>	18.72	1.33	32.59
<i>Masking</i>	28.16	1.80	88.90
<i>A-weight. ANC</i>	18.34	1.32	30.59
<i>ANC+Masking</i>	20.18	1.19	33.12

Table 4.7 Objective psychoacoustic evaluations for -10 dB SNR

Scenario/Evaluation type	Loudness, sones	Sharpness, acum	Roughness, asper
--------------------------	-----------------	-----------------	------------------

<i>Original</i>	25.98	1.91	64.53
<i>Psych. ANC</i>	19.52	1.53	46.72
<i>Conv. ANC</i>	21.46	1.56	48.67
<i>Masking</i>	31.15	2.02	91.04
<i>A-weight. ANC</i>	19.01	1.48	41.32
<i>ANC+Masking</i>	22.98	1.26	49.11

According to the previous studies [113], loudness noticeable difference is about 2 sones, sharpness noticeable difference is about 0.2– 0.3 acum and roughness noticeable difference is about 2.5 asper.

Loudness evaluations show that ANC algorithms without masking have better loudness reduction and the A-weighting psychoacoustic ANC algorithm has the best loudness evaluations for all SNR scenarios. However, it is obvious that masking algorithms have higher loudness than ANC only algorithms because the target audio is amplified in order to mask out the high-frequency and residual noise. Therefore, it is possible to conclude that pure masking algorithms are not suitable for headphones noise reduction because it can make sound dangerously loud in cases of low SNR level. However, the proposed integrated psychoacoustic ANC and masking algorithm does not have very significant loudness differences in comparison with ANC only algorithms for all SNR scenarios because masking is used only in the high-frequency range. Moreover, it is necessary to note that ANC algorithms reduce only low-frequency noise and high-frequency noise components are still presented in the output signal. The proposed integrated system has louder output because of the amplification of the target audio in order to mask out high-frequency noise. Therefore, the proposed integrated system output makes the sound even more pleasant because high-frequency noise becomes inaudible or less audible. Sharpness evaluations show that our proposed integrated system has the best results. It is possible to explain in the following way. Psychoacoustic ANC algorithm reduces low-frequency audible noise at first, inaudible noise components haven't any influence on the psychoacoustic evaluations. Psychoacoustic masking algorithm masks out the high-frequency noise and, as was mentioned above, the masking algorithm has frequency and time averaging procedures, which makes the amplified target audio smooth and reduces sharpness level. The

ANC only algorithms suffer from high-frequency performance. Therefore, high-frequency noise still has a higher level than the target audio, especially for cases of -5 and -10 dB SNR, and the sound is sharper. Roughness evaluations have a similar situation as loudness. A-weighting psychoacoustic ANC algorithm has better sharpness evaluations. The proposed integrated system has better performance in comparison with masking only, but poorer performance in comparison with ANC only algorithms. The description is similar to loudness evaluations. The proposed integrated system has higher roughness than ANC only algorithms, but the difference is not very significant.

4.2.3 Subjective Evaluations

Subjective perceptual tests [114] are more important for real-life headphones applications with psychoacoustic algorithms. Subjective listening evaluations are noise audibility and pleasantness quality of sound. The 5 scores systems for two subjective perceptual evaluations are introduced. It was decided to implement subjective evaluations in the following way. The first one shows the possibility of a person to hear the noise after processing and to compare the audibility of noise and target audio signal of the final output signals of each noise reduction approach. The scores and their descriptions are shown in Table 4.8.

The second subjective evaluation shows the pleasantness level of the output signal (distortions of the target audio). The scores and their descriptions are shown in Table 4.9. The main idea of this work is to improve perceptual results and to show that inaudible noise has not any influence on the human's perception. 22 participants took part in subjective experiments, the ages of the participants are between 21-33 years old. All participants have no hearing problems. Subjective tests took part in the soundscape room in order to reduce the possibility of outside sound influence. Participants were able to listen to recorded tracks after different noise reduction approaches in random for three SNR scenarios. Each participant manually calibrates the sound level based on his/her hearing preferences. The clear target audio and the target audio and

primary noise for different SNR levels were also provided for comparisons. Beyerdynamic Custom One Pro Plus headphones were used as a source of the signals to compare them. The results of subjective evaluations for three SNR levels are presented in Tables 4.10 – 4.12.

Table 4.8 Noise inaudibility scores system [91]

Scores	Description
1	Noise is audible. Target audio is inaudible.
2	Noise is better audible than audio.
3	Noise and audio are both audible on the same level.
4	Target audio is better audible, but noise is still audible too.
5	Noise is inaudible.

Table 4.9 Pleasantness scores system [91]

Scores	Description
1	The sound is very annoying. High-level distortions of the target audio or high noise
2	Sound is annoying. Some distortions of the target audio or high-level noise.
3	Sound is not natural. Some artifacts are audible or poor noise reduction.
4	Sound is good. No distortions. Low-level residual background noise is audible.
5	Sound is good and natural. Without any effects.

Table 4.10 Subjective psychoacoustic evaluations for 0 dB SNR

Scenario/Evaluation type	Noise inaudibility score	Pleasantness scores
<i>Original</i>	2.55	2.37
<i>Psych. ANC</i>	3.73	3.46
<i>Conv. ANC</i>	3.55	3.54
<i>Masking</i>	3.55	2.82
<i>A-weight. ANC</i>	3.74	3.64
<i>ANC+Masking</i>	4.65	4.55

Table 4.11 Subjective psychoacoustic evaluations for -5 dB SNR

Scenario/Evaluation type	Noise inaudibility score	Pleasantness scores
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<i>Original</i>	2.27	1.91
<i>Psych. ANC</i>	3.46	3.37
<i>Conv. ANC</i>	3.64	3.45
<i>Masking</i>	3.10	2.46
<i>A-weight. ANC</i>	3.19	3.82
<i>ANC+Masking</i>	4.47	4.18

Table 4.12 Subjective psychoacoustic evaluations for -10 dB SNR

Scenario/Evaluation type	Noise inaudibility score	Pleasantness scores
<i>Original</i>	1.73	1.55
<i>Psych. ANC</i>	3.27	2.91
<i>Conv. ANC</i>	3.09	2.90
<i>Masking</i>	2.27	1.92
<i>A-weight. ANC</i>	3.10	3.18
<i>ANC+Masking</i>	4.20	3.97

Average scores, which are presented in Tables 4.10 – 4.12 show that the proposed integrated system has better subjective scores for all SNR scenarios. Differences in subjective scores for 0 dB SNR are not very significant, but with decreasing of SNR subjective scores for all approaches also decrease. However, the proposed integrated system has better subjective scores in both terms and scores are still be high even for -10 dB SNR case. Therefore, it is possible to state that the proposed integrated psychoacoustic ANC and masking system has a better perceptual quality of the output signal in terms of noise audibility and pleasantness of sound, which implies that this system is more efficient and suitable for headphones noise reduction applications. Moreover, the proposed noise reduction system is based on the improvement of the

perceptual quality of sound, which is the most important parameter. In addition, it is possible to find some relations between subjective scores and objective evaluations. Loudness is a parameter, which is not so related to subjective scores as roughness and sharpness. It is possible to explain in the following way. Loudness parameter estimates the perceptual sound level and does not take into account the type and content of the sound. However, sharpness and roughness are parameters based on the frequency content, SPL of different frequency components and relations between frequency components. Therefore, objective evaluations of sharpness and roughness are more related to human's understanding of pleasantness sound. The algorithms with lower values of roughness and sharpness have better subjective pleasantness scores. Especially, psychoacoustic ANC and conventional subband ANC algorithms have very close values of sharpness and roughness for all scenarios and it is possible to see that pleasantness scores are also similar.

4.2.4 Advantages and Disadvantages of Compared Approaches

The advantages and disadvantages of each of the methods tested and their average subjective and objective scores are summarized in this section. Average objective and subjective scores are estimated among all subjective evaluations and objective evaluations for all SNR scenarios and all compared approaches. In Table 4.13, average subjective scores, average objective scores, advantages, and disadvantages of all compared noise reduction approaches are shown. Average objective evaluations consist of three parameters (loudness, sharpness, and roughness) and their average values across three SNR scenarios. Average subjective scores consist of average values of inaudibility of noise and sound pleasantness evaluations across three SNR scenarios. As was mentioned above, the proposed integrated system achieved a better perceptual quality of the target audio sound. Results from Table 4.13 summarize and simplify all results from Tables 4.10 – 4.13. It is possible to see from Table 4.13, that the proposed ANC + Masking method has more advantages in comparison with others, the most significant is the efficiency for broadband noise reduction.

Table 4.13 Advantages and disadvantage of noise reduction approaches [91]

Method	Objective evaluations	Subjective evaluations	Advantages	Disadvantages
<i>Conv. Subband ANC</i>	<i>Loud:</i> 19.53 <i>Sharp:</i> 1.36 <i>Rough:</i> 36.71	<i>Inaud.:</i> 3.43 <i>Pleas.:</i> 3.3	1.High convergence rate; 2.Efficient for low-frequency noise;	1.Not efficient for high-frequency noise; 2.Not take into account perceptual properties of hearing system.
<i>A-weighting ANC</i>	<i>Loud:</i> 18.56 <i>Sharp:</i> 1.34 <i>Rough:</i> 32.98	<i>Inaud.:</i> 3.34 <i>Pleas.:</i> 3.55	1.Efficient for low-frequency noise; 2.Take into account perceptual properties of hearing system;	1.Not efficient for high-frequency noise;
<i>Masking</i>	<i>Loud:</i> 28.87 <i>Sharp:</i> 1.84 <i>Rough:</i> 85.28	<i>Inaud.:</i> 2.97 <i>Pleas.:</i> 2.4	1.Take into account perceptual properties of hearing system; 2.The lowest computational complexity;	1.Not useful for low SNR level;
<i>Psych. ANC</i>	<i>Loud:</i> 18.81 <i>Sharp:</i> 1.37 <i>Rough:</i> 35.43	<i>Inaud.:</i> 3.49 <i>Pleas.:</i> 3.25	1.Take into account perceptual properties of hearing system; 2.Reduce only audible noise;	1.Not efficient for high-frequency noise;

<i>ANC+Masking</i>	<i>Loud: 20.95</i> <i>Sharp: 1.2</i> <i>Rough: 37.15</i>	<i>Inaud.: 4.44</i> <i>Pleas.: 4.23</i>	1.Take into account perceptual properties of hearing system; 2.Reduce only audible noise; 3.Efficient for broadband noise;	1.High complexity for real-prototype implementation;
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4.3 Conclusions

In this chapter, a new integrated psychoacoustic subband ANC and psychoacoustic masking system for headphones was proposed. The main contribution of this chapter is the integration of the psychoacoustic subband ANC and psychoacoustic masking system in order to achieve better noise reduction in a wider frequency range and to get a better perceptual quality of the output signal. The same psychoacoustic model was used for the psychoacoustic ANC and masking system. Psychoacoustic ANC algorithm operates at the low-frequency range, which is the most sensitive for the human's hearing system, and masking is used as an additional stage in order to mask out the residual and high-frequency noise. Subjective and objective psychoacoustic evaluations proved the efficiency of the proposed system. Moreover, it is possible to see the relationship between subjective and objective psychoacoustic evaluations, which helps to highlight the advantages of integrated psychoacoustic ANC and psychoacoustic masking system.

Chapter 5

Binaural and Combined Bilateral/Binaural ANC Algorithms for Headphones

This chapter proposes a new binaural ANC algorithm for headphones. The noise-cancellation headphones performance degrades for the multiple-noise sources scenarios. Moreover, noise sources' directions influence ANC system performance. Therefore, this chapter focuses on the improvements of multiple-noise sources performance for ANC headphones applications. The idea of the binaural ANC algorithm is based on the advantage of both channels' interaction. A comparison of the proposed binaural ANC algorithm with a conventional bilateral ANC approach leads to the next part of this chapter, which presents a new combined bilateral/binaural ANC approach. The proposed algorithm is evaluated in a closed-back ANC headphones prototype. The experimental results prove the efficiency of the proposed algorithm for headphones applications.

5.1 Binaural ANC Algorithm

This section describes a new binaural ANC algorithm for headphones [115]. There are many commercial implementations of ANC headphones and many ANC headphones algorithms. However, most existing feedforward ANC headphones algorithms do not use features and advantages of the binaural behavior of the human's hearing system. Most of the proposed feedforward ANC headphones use only one reference microphone, situated at one of the ear cups; and with an error microphone situated inside each ear cup. The same noise control signal is used for both channels. Such an approach cannot guarantee high noise reduction performance in the cases of multiple noise sources from different directions. The head-shadow effect is not taken into account and the reference signal from one channel is not used in another channel. To solve this issue, some feedforward ANC algorithms for headphones are implemented in the conventional bilateral solution, where each channel has its reference and error microphones, and the ANC algorithm is applied independently to each channel. Therefore, there are two independent monaural ANC systems with their reference and error microphones, and secondary sources without any interaction between these channels. Conventional bilateral ANC algorithm for headphones has high noise reduction performance for the single noise source. However, its performance decreases in the case of multiple noise sources situated at different locations [100]. These results are validated in the following sections. It is possible to explain by the effect of different HRTFs and head-shadow effect, which implies that the reference signal of one channel does not always provide enough information for good noise cancellation on both sides. Real-life noise scenarios usually consist of multiple noise sources from the different directions presented at the same time. Therefore, the bilateral ANC solution is not always efficient for the aggressive noisy environment. As was mentioned in [23], the number of reference microphones has an influence on the ANC performance for the multiple noise sources cases. The interaction between two channels of ANC headphones artificially increases the number of reference microphones for each channel processing. Thus, it is assumed that

the binaural ANC algorithm should improve performance for multiple noise sources.

5.1.1 Binaural FxNLMS Algorithm

The proposed binaural ANC algorithm [116] is based on the binaural noise reduction algorithm for hearing aids [62], which was described in Chapter 2. It was mentioned, that the noise reduction algorithm for hearing aids cannot be directly applied for the ANC algorithm because the acoustic part of the secondary path is ignored in the hearing aids approach [117]. Thus, the first milestone is the development and implementation of a binaural FxNLMS algorithm for ANC algorithm needs. Hearing aids binaural noise reduction approach is based on a fixed optimal Wiener filter. Binaural noise reduction technique for hearing aids shares filters' inputs from microphone arrays between two channels and, also, shares Wiener filters' coefficients [118]. Therefore, firstly, 4 possible binaural ANC implementations are investigated in order to find the optimal solution. Table 5.1 shows 4 different versions of binaural ANC algorithms.

The primary goal is to compare all the proposed binaural ANC implementations with the conventional (bilateral) ANC approach to define the best solution. Comparisons are conducted based on Matlab simulations using actual measured primary and secondary paths and HRTFs of a dummy head for different directions. Firstly, comparisons are made for the single noise source placed in front of the dummy head (0° direction) at a distance of 1.5 m from the center of the dummy head. Two noise sources are used for the first comparisons: tonal noise of 500 Hz and broadband white noise 300-600 Hz. Noise sources levels are aligned at 70 dB SPL at the center of the dummy head. According to the simulation results, versions 2 and 4 diverge for both noise sources for a single noise source case. The 3rd version is the closest to bilateral ANC algorithm results.

However, the bilateral ANC algorithm is still better in these experiments. Based on the primary results, the sharing of the FxNLMS inputs causes divergence of

the algorithm. Therefore, it was decided to continue the investigation to find the best binaural ANC implementation.

Table 5.1 Possible variations of binaural ANC implementations

No	Filters' coefficients	FxNLMS input
1	Sharing filters' coefficients (One joint filter coefficients vector)	Independent FxNLMS inputs
2	Sharing filters' coefficients (One joint filter coefficients vector)	Sharing FxNLMS inputs (One joint FxNLMS inputs vector)
3	Independent filters' coefficients	Independent FxNLMS inputs
4	Independent filters' coefficients	Sharing FxNLMS inputs (One joint FxNLMS inputs vector)

As was mentioned above, it is assumed that the binaural ANC algorithm should have better results for multiple noise sources. Noise sources are placed at different positions. Broadband white noise is placed in front of a dummy head (0° degree direction) and tonal noise is placed at the right side of a dummy head (90° degree direction). Figure 5.1 shows the direction of noise sources.

The comparisons are conducted for the same 4 binaural ANC versions and bilateral conventional ANC algorithm. Bilateral ANC algorithm has better noise reduction performance for the right channel. It can be easily explained that since the tonal noise is placed at the right side and tonal noise reaches the right reference microphone faster than the right error microphone, which improves the right channel's situation. However, the major focus of these experiments is to compare different binaural ANC versions. According to the simulation results, it is possible to state that the 4 proposed binaural ANC versions are not efficient and cannot be used because bilateral ANC always has better noise reduction results. Therefore, it is necessary to continue the investigation and develop a new binaural ANC algorithm.

It is necessary to note that only the 3rd version of the binaural ANC algorithm converges for multiple noise sources case. This version assumes the sharing of only reference signals. However, the performance of the 3rd binaural ANC algorithm version is very poor compare to bilateral implementation. It can be due to the content of sharing reference signals and individual independent FxNLMS

inputs, which are quite different is this way of implementation. Sharing of filters' coefficient is not necessary because the adaptive approach is used in this work and filters update their coefficients according to the input data. Hearing aids binaural noise reduction approach shares filters' coefficients because it is based on an optimal fixed Wiener filter.

Figure 5.1 – Multiple noise source experimental arrangement

According to this reasoning, version 4 should have the best result, because this version assumes sharing of references and FxNLMS inputs and independent filters. However, the 4th version diverges for all cases. Thus, a theoretical investigation to find the issues in the proposed methods and to develop the new binaural ANC implementation is developed in this chapter.

The major question is: “Why sharing of FxNLMS inputs causes divergence of the algorithm?”. As was mentioned in Chapter 2, the convergence of ANC algorithms strictly depends on the primary and secondary paths, which is reflected in (2.1). Therefore, when FxNLMS inputs are shared after passing through different (right and left) estimated versions of the secondary path and then noise control signals pass, independently, through the right secondary path for the right channel noise control and the left secondary path for the left channel noise control, it causes divergence and instability because of the left and right secondary paths difference. Therefore, a new binaural ANC algorithm is proposed and based on these theoretical assumptions. The first step is the stacking of the right and the left reference signals into one joint reference signal.

$$\mathbf{x}^{Bin}(n) = [\mathbf{x}_L^T(n) \mathbf{x}_R^T(n)]^T, \quad (5.1)$$

Where $\mathbf{x}_L(n) = [x_L(n) x_L(n-1) \dots x_L(n-N+1)]^T$ and $\mathbf{x}_R(n) = [x_R(n) x_R(n-1) \dots x_R(n-N+1)]^T$.

Adaptive filters are still independent for both channels and update filter coefficients based on the input data. The main part of the binaural ANC algorithm is a binaural FxNLMS implementation. The FxNLMS filter inputs are also stacked into one joint input vector. Both reference signals are passed through the corresponding estimated version of the secondary path before the stacking procedure. The binaural FxNLMS algorithm is expressed as follows. The right channel adaptive filter input is formed as the stacked vector of the right and left reference signals passing through the estimated right secondary path $\hat{\mathbf{s}}_R(n)$:

$$x'_{RR}(n) = \hat{\mathbf{s}}_R(n) * \mathbf{x}_R(n), \quad (5.2)$$

$$x'_{RL}(n) = \hat{\mathbf{s}}_R(n) * \mathbf{x}_L(n), \quad (5.3)$$

$$\mathbf{x}_R'^{Bin}(n) = [\mathbf{x}_{RR}'^T(n) \mathbf{x}_{RL}'^T(n)]^T. \quad (5.4)$$

Similar stacking is also implemented in the left channel adaptive filter using the left estimated secondary path $\hat{\mathbf{s}}_L(n)$. The binaural FxNLMS algorithm uses the binaural adaptive filter inputs is shown below:

$$\mathbf{w}_i(n+1) = \mathbf{w}_i(n) + \mu \frac{e_i'(n) \mathbf{x}_i'^{Bin}(n)}{\|\mathbf{x}_i'^{Bin}(n)\|^2}, \quad (5.5)$$

where i is the index, which defines the channel L (left) or R (right).

The last stage of the binaural ANC algorithm is the filtering of the reference signals by the adaptive filter. Filtering procedures are similar for both channels and use the same joint reference signal (5.1):

$$y_i = \mathbf{w}_i(n) * \mathbf{x}^{Bin}(n). \quad (5.6)$$

Figure 5.2 shows the block diagram of the proposed binaural integrated audio ANC algorithm. Matlab simulations are conducted to prove that the proposed binaural ANC algorithm is able to work. The same noise sources scenarios are

used as for the previous simulation experiments. Tables 5.2 and 5.3 show the simulation results for single and multiple noise sources, respectively. Single noise source results show a similar performance of bilateral and binaural ANC algorithms. The noise source is placed in front of the dummy head. Therefore, it was expected that for this case both ANC algorithms should have similar results. The noise source is placed at the 0° position, therefore both ears receive the noise signal under the similar conditions.

Figure 5.2 – Block diagram of the proposed binaural integrated audio ANC algorithm [116]

Table 5.2 Simulation noise reduction results of the proposed binaural ANC and bilateral ANC algorithms for single noise source

Noise type	Tonal		Broadband	
ANC ver./Ch.	Left	Right	Left	Right
Bilateral	-59.0 dB	-58.0 dB	-17.2 dB	-17.3 dB
Binaural	-58.1 dB	-58.2 dB	-16.2 dB	-16.7 dB

Table 5.3 Simulation noise reduction results of the proposed binaural ANC and bilateral ANC algorithms for multiple noise sources

ANC ver./Ch.	Left	Right
Bilateral	-11.0 dB	-14.4 dB
Binaural	-12.5 dB	-14.0 dB

Thus, both references are quite similar. The results from the multiple-noise source experiments show that the binaural ANC algorithm improves the performance of the “worst” left channel, as one noise source is placed at the 0° position and another - at the 90° position (right side). The major focus of this section is on the definition and development of a workable binaural ANC algorithm for headphones. Therefore, further investigations and real-time experiments and comparisons are presented in the following sections.

5.1.2 Theoretical Considerations of Binaural ANC Algorithm

The performance of the ANC algorithm strictly depends on the coherence [119] between desired signal $d(n)$ and reference signal $x(n)$ [30]. Coherence is expressed as follows:

$$C_{ab}(f) = \frac{|G_{ab}(f)|^2}{G_{aa}(f)G_{bb}(f)}, \quad (5.7)$$

where a and b are two different signals, f is frequency, $G_{ab}(f)$ is the cross-spectral density between a and b , and $G_{aa}(f)$ and $G_{bb}(f)$ the auto-spectral density of a and b .

Coherence between the desired signal at the error microphone and reference signal at the reference microphone can be used to estimate the upper boundary of the highest possible noise reduction level of ANC algorithm based on optimal fixed Wiener filter [30]. Theoretical noise reduction can be expressed by the following equation:

$$A(f) = 10 \log_{10}[1 - C_{ErrRef}(f)], \quad (5.8)$$

where $C_{ErrRef}(f)$ is the coherence between primary noise at the error and reference microphones. It is obvious from (5.8) that higher coherence value leads to higher noise reduction performance.

It is possible to assume that there are noise environmental scenarios, where the coherence between one channel's desire signal and another channel's reference signal will be higher than direct-channel coherence. It can be caused by many environmental factors, such as different noise sources positions and their numbers, room reverberation, physical constructions, and buildings.

Therefore, it is expected that the proposed binaural ANC algorithm should achieve higher noise reduction performance for some of the environmental noise scenarios, based on the coherence theoretical studies.

The next observed theoretical study is about the ANC causality issue [120]. The simplest assumption about noise sources directions, which can cause causality issue, is based on the cases, where noise sources are placed at the one side (right or left) of the head. For example, if the noise source is placed on the right side, it is quite obvious that primary noise reaches the left error microphone faster than the left reference microphone. Therefore, the reference signal does not have any time advantage correspond to the desired signal at the error microphone. Thus, it is possible to meet the causality issue. For more complicated cases, it is well-known that to satisfy the ANC algorithm causality needs group delay of the acoustic primary path should be higher than the group delay of the digital and acoustic secondary path. Figure 5.3 describes the causality situation for the ANC algorithm.

Moreover, in the previous studies [22] it was shown that if amplitudes of noise and noise control signal are the same, phases difference cannot exceed 60° between these two signals. Otherwise, high noise reduction performance cannot be guaranteed. Figure 5.4 shows this case.

Figure 5.3 – Block diagram description of primary and secondary paths group delays

Figure 5.4 – Phase difference requirements to satisfy the causality issue for the ANC algorithm

Moreover, the group delays of the primary and secondary paths for two variations of headphones wearing, tight (proper wearing) and loose (not proper wearing), was examined in [22]. It is obvious from [22] that even for the tight wearing, the group delay of the secondary path is higher for the low-frequencies, which leads to non-casual situations and high noise reduction level cannot be achieved. In [121], it was shown how casual and non-casual delays influence the ANC headphones performance.

From (2.1), it becomes obvious that the optimal Wiener filter for this case can be expressed as follows:

$$W_{opt}(z) = z^{-(\Delta_p - \Delta_s)} = z^{-\Delta}, \quad (5.9)$$

where Δ_p and Δ_s are the delay in samples of the primary and secondary paths, respectively.

The causality requirement is satisfied when $\Delta_p - \Delta_s = \hat{\partial} \geq 0$. Non-casual delay defines as $\Delta_p - \Delta_s = \hat{\partial} < 0$. It is shown that overall noise reduction can be expressed as follows:

$$\eta = 10 \log_{10} \frac{r_q(0)}{r_q(0) - \mathbf{r}_{\hat{\partial}}^T \mathbf{R}_q^{-1} \mathbf{r}_{\hat{\partial}}}, \quad (5.10)$$

where r_q is the autocorrelation element of $q(n)$, which equal to $d(n-\partial)$; $\mathbf{R}_q$ is the autocorrelation matrix; $\mathbf{r}_\partial$ is the autocorrelation vector, which starts from ∂ . In [122], it was shown that increasing of non-casual delay leads to decreasing of the noise reduction performance and primary noise bandwidth, which can be reduced.

Theoretical noise reduction evaluation based on causality is more complicated for time-varying primary and secondary paths. It was shown in [22] that for time-varying primary and secondary paths, the causality situation strictly depends on the primary path delay. Also, it was mentioned that increasing the adaptive filter order cannot improve the performance of the non-casual system. Moreover, ANC headphones were tested for two different noise source directions 0° and 90° . It was found that the ANC headphones system is non-casual for 90° direction for the left channel. The causality issue can be solved by changing in the configuration or using of additional reference microphones. Therefore, the proposed binaural ANC algorithm, which uses both reference microphones (the right and the left) for each channel processing should be useful in terms of solving causality issue for some specific noise source directions. Binaural ANC algorithm combines both features, which can help to improve the noise reduction performance of ANC headphones. Firstly, the number of reference microphones are artificially increased, which implies that it is possible to use more noise information. Moreover, both reference microphones are placed on opposite sides. Thus, one side reference can have a necessary time advantage compared to the opposite channel's desire signal, which can improve performance for this channel.

5.1.3 Single Noise Source Scenarios

Firstly, a new proposed binaural ANC algorithm is tested on the single noise source scenarios to check its performance and to compare with conventional bilateral ANC algorithm. It is not expected that the binaural ANC algorithm will have much better results compared with the bilateral ANC algorithm. However, it is assumed that the binaural ANC algorithm can be helpful in causality issues

solution. To prevent the causality issue, the group delay of the secondary path should be less than the group delay of the primary path [87]. For the headphones case, the causality issue can be caused by many different factors such as improper headphones wearing, directions of the noise sources and etc. In the previous study [22], it was shown that causality issues are actual for low-frequency range in headphones applications. Also, in [116], it was shown that the causality issue appears in the one channel (left or right) when the noise source is situated on the opposite side. In this case, primary noise reaches the error microphone faster than the reference microphone. Therefore, it is assumed that the binaural ANC algorithm should improve noise reduction performance for the “worst” ear, in the case when the noise source is placed from the left or right side. In this case, sharing the reference signal from the nearer to the noise source channel can help to solve the causality issue of the far channel, because of its time advantage.

All real-time experiments are conducted in the anechoic chamber. Real-time processing was carried out using the Texas Instruments TMS320C6713DSK development board, with an additional two daughter analog-to-digital/digital-to-analog boards DSK6713IF-A and MSPAMP800, which provide adjustment of gains for error and reference microphones and noise control sources independently. DSP board details are presented in Appendix A. The Beyerdynamic Custom One Pro Plus headphones (with no embedded ANC functionality) is used for our ANC system experiments. Each ear cup consists of a MEMS [123] reference microphone (attached to the external of the ear cup), and a MEMS error microphone (attached to the internal of the ear cup). The ANC system operates at a sampling rate of 16 kHz, and the 400-tap adaptive filter is used for binaural and bilateral ANC implementations. However, before starting real-time experiments, it is necessary to define the optimal construction of ANC headphones in terms of microphones positions. The reference microphone position is not so significant for the ANC algorithm, but the position of error microphone has a direct and strict influence on the secondary path responses. In [32] study, it was explained that smooth and flat impulse and frequency responses of the secondary path help to get higher noise reduction results and a more stable algorithm. Therefore, 4 different positions of the error

microphone are investigated to define the best position. Figure 5.5 shows possible positions of error microphone regarding the human's ear. Error microphone is embedded in headphones ear cup for positions #1 – #3. In these configurations, the error microphone is placed near to the headphones' emitter (secondary source), which implies that secondary path responses should be flat and smooth [124]. Moreover, the short acoustic part of the secondary path decreases the group delay of the secondary, which is useful to solve the causality issues. In position #4, the error microphone is placed inside the ear of the dummy head. This position is also investigated in order to check any significant difference in the secondary paths' responses.

Figure 5.5 – Error microphone positions; 1 – 3 positions embedded in ear cups of headphones and position 4 inside the ear.

Figure 5.6 and 5.7 present the impulse and frequency responses of both channels for all 4 positions, respectively. Impulse responses are very similar for positions #1 – #3. Position #4 impulse response has a bigger amplitude difference. However, frequency responses are more useful for the best position definition. Frequency responses of both channels for all error microphones positions are compared. It was decided to choose Position #1 because the frequency responses of secondary paths are quite smooth and flat at the main hearing range till 4000 Hz. Moreover, frequency responses between the right and left channel are more similar for Position #1, which can be useful for binaural ANC algorithm.

Figure 5.6 – Impulse responses of secondary paths for 4 error microphone positions; Position #1 – blue, Position #2 – black, Position #3 – Red and Position #4 - green

Figure 5.7 – Frequency responses of secondary paths for 4 error microphone positions; Position #1 – blue, Position #2 – black, Position #3 – Red and Position #4 - green

Moreover, frequency responses of two channels secondary paths are the most similar for Position #1, which is useful for the proposed binaural ANC algorithm and can help to achieve a better balance in noise reduction between channels. A reference microphone is placed at the center of the ear cup (outside) to get the maximum possible distance between microphones. The positions of the microphones are shown in Appendix B.

As was mentioned above, all real-time experiments took part in the anechoic chamber. KEMAR dummy head [125] is placed in the middle of the anechoic chamber. Genelec speakers [126] are used to play the noise signal. The experimental arrangement is shown in Appendix B.

The first aim of these experiments is to prove that previously proposed binaural ANC implementation is able to work for different real-time cases. The second aim is to prove the theoretical assumption that the binaural ANC algorithm should improve noise reduction performance of the “worst” (opposite to the noise source) channel [127].

Broadband noise source (300 – 1000 Hz), placed at three different directions, is used for single source real-time experiments. The following directions are used: 0° (front of the dummy head), 90° (the right side) and 180° (behind of the dummy head). Noise source has 75 dB SPL at the center of the dummy head. Table 5.4 shows the results of a single noise source, placed at different directions, real-time experiments for bilateral and binaural ANC algorithms.

Table 5.4 Real-time noise reduction results of binaural ANC and bilateral ANC algorithms for single broadband noise source from different directions

Directions	0° direction		90° direction		180° direction	
Ch./ANC type	Left	Right	Left	Right	Left	Right
Bilateral	-14.9 dB	-14.3 dB	-10.2 dB	-15.5 dB	-12.5 dB	-12.7 dB
Binaural	-14.5 dB	-14.0 dB	-13.1 dB	-15.1 dB	-12.4 dB	-12.8 dB

As was expected, noise reduction performances of binaural and bilateral ANC algorithms are similar for 0° and 180° directions. It can be explained by the fact that neither of the channels has a time advantage and the causality situation is still the same for both channels because noise source is placed at the frontal and behind positions. Binaural ANC algorithm helps to improve the performance of the “worst” left channel for 90° noise source direction. The right reference signal has a significant time advantage compared to the primary noise at the left error microphone. Therefore, the right reference helps to improve the causality situation for the left channel. Noise reduction improvement for the “worst” channel is about 3 dB. It can be assumed that the left reference should degrade the performance of the right channel. However, the degradation is about 0.5 dB because the right channel still uses the right reference, which is dominating the left reference in terms of amplitude level and time advantage.

During this research work, J. Cheer published similar ANC algorithms [128], called a multi-reference ANC algorithm for headphones. The idea is to apply two

adaptive filters per channel: direct channel filter and cross-channel filter. References are independent and are defined in a similar way as for conventional ANC algorithm $x_L(n)=[x_L(n)x_L(n-1)...x_L(n-N+1)]$ and $x_R(n)=[x_R(n)x_R(n-1)...x_R(n-N+1)]$. The following equations and descriptions are presented for the right channel. The left channel procedure is the same. The FxLMS inputs are similar as were proposed in the binaural ANC algorithm (5.2) – (5.3). However, they are not stacked in one joint FxLMS input. The multi-reference ANC algorithm requires two adaptive filters per channel based on direct- and cross-channel inputs. Therefore, FxLMS procedure for multi-reference ANC algorithm is expressed as follows:

$$\mathbf{w}_{RR}(n+1) = \mathbf{w}_{RR}(n) + \mu e_R(n) \mathbf{x}_{RR}'(n), \quad (5.11)$$

$$\mathbf{w}_{RL}(n+1) = \mathbf{w}_{RL}(n) + \mu e_L(n) \mathbf{x}_{RL}'(n). \quad (5.12)$$

Two adaptive filters produce two noise control signals. The final noise control signal is formed by the summation of two noise control signals.

$$y_{RR}(n) = \mathbf{w}_{RR}(n) * \mathbf{x}_R(n), \quad (5.13)$$

$$y_{RL}(n) = \mathbf{w}_{RL}(n) * \mathbf{x}_L(n), \quad (5.14)$$

$$y_R(n) = y_{RR}(n) + y_{RL}(n). \quad (5.15)$$

In other words, the multi-reference ANC algorithm has independent input signals and joint output (noise control) signal. Figure 5.8 shows the block diagram of the multi-reference ANC algorithm for one channel. The proposed binaural ANC algorithm has joint inputs and independent output. The main focus of Cheer's study is to compare the conventional bilateral ANC algorithm with a multi-reference ANC algorithm for a single noise source in order to prove that the multi-reference ANC algorithm improves noise reduction for the “worst” channel. Therefore, it was decided to repeat his algorithm in simulations and compare it with bilateral and the proposed binaural ANC algorithm performances. J. Cheer conducted real-time experimental his paper. The experimental setups are shown in Table 5.5

Figure 5.8 – Block diagram of multi-reference ANC algorithm (right channel only)

Table 5.5 Experimental setup of multi-reference ANC algorithm [128]

Single Noise Source:	Pink Noise (0-8 kHz)
Directions:	0°, 90°, 180° and 270°
Distance:	1.3 m
Direct-channel filter order	160 taps
Cross-channels filter order	320 taps
Total filter order for two channels	2x160 + 2x320 = 960 taps

The order of cross-channel filters is two times bigger than the direct-channel filters' order. In [128], it was shown that filters' orders were chosen according to get the highest possible noise reduction performance. The proposed binaural ANC algorithm is compared with the multi-reference ANC algorithm based on Matlab simulations. However, comparisons are conducted based on our setups for real-time experiments. The noise source is the same as was used in [128], pink noise 0 – 8 kHz. Distance is 1.5 meters from the head. Three noise source directions 0°, 90° and 180° are used. Filters' orders are selected from binaural real-time experiments. Table 5.6 shows the number of filters and their orders for bilateral, binaural and multi-reference ANC algorithms, compared in this experiment.

Noise reduction results are presented in Table 5.7. Binaural and multi-reference

ANC algorithms improve noise reduction performance of the “worst” left a channel for 90° direction case, as was stated in [128] and was proved above. For 0° and 180° directions, binaural and multi-reference ANC algorithms show very similar results as the conventional bilateral ANC algorithm. Multi-reference ANC algorithm improves noise reduction performance slightly better for the “worst” channels, it is about 5.5 dB and binaural ANC – 4 dB. The multi-reference ANC algorithm has a small advantage for all cases. It can be explained by the larger number of filters and higher total filters’ order, used in multi-reference ANC algorithm. Therefore, it is possible to state that both, multi-reference and the proposed binaural ANC algorithms, are efficient and have very similar results. Their advantage is getting higher noise reduction performance of the “worst” channel by using the reference signal from the “best” channel, which helps to improve the causality situation. However, the proposed binaural ANC algorithm achieves similar results, but it requires less computational sources.

Table 5.6 Simulations setup for bilateral, binaural and multi-reference ANC algorithms

ANC type	Bilateral	Binaural	Multi-reference
Number of filters per channel	1 filter	1 filter	2 filters
Order of filter per channel	1x400 = 400 t.	1x400 = 400 t.	1x400 + 1x800 = 1200 t.
Total number of filters	2 filters	2 filters	4 filters
Total filters’ order	2x400 = 800 t.	2x400 = 800 t.	2x400 + 2x800 = 2400 t.

Table 5.7 Simulations noise reduction results for bilateral, binaural and multi-reference ANC algorithms

Direction	0°		90°		180°	
ANC type/Ch.	Left	Right	Left	Right	Left	Right
Bilateral	-16.1 dB	-16.5 dB	-11.2 dB	-17.3 dB	-14.5 dB	-14.9 dB
Mult.- ref.	-16.0 dB	-16.7 dB	-16.7 dB	-17.1 dB	-15.0 dB	-15.0 dB
Binaural	-15.9 dB	-16.2 dB	-15.4 dB	-16.9 dB	-14.4 dB	-14.9 dB

The next comparison stage is based on transfer functions from the desired signal $d(n)$ to the noise control signal $y'(n)$. The main purpose is the theoretical comparison between the proposed binaural ANC algorithm and the multi-reference ANC approach. The transfer function analysis is easier to conduct using the narrowband noise source [129]. Therefore, tonal noise is used for this

theoretical estimation. Firstly, the transfer function for the multi-reference ANC algorithm for the left channel is presented. The left and right reference signals are expressed in the following way:

$$x_{Rk}(n) = A_R \cos(w_{R0}n + \theta_{Rk}) = \frac{A_R}{2} (e^{jw_{R0}n} e^{j\theta_{Rk}} + e^{-jw_{R0}n} e^{-j\theta_{Rk}}), \quad (5.16)$$

$$x_{Lk}(n) = A_L \cos(w_{L0}n + \theta_{Lk}) = \frac{A_L}{2} (e^{jw_{L0}n} e^{j\theta_{Lk}} + e^{-jw_{L0}n} e^{-j\theta_{Lk}}), \quad (5.17)$$

where w_{L0} and w_{R0} are the frequencies of the left and right narrowband noise signals, captured by reference microphones, k and n are the coefficient and time index, A_L and A_R are the amplitudes of the references.

The update of individual coefficients of two adaptive filters:

$$W_{LLk}(z) = \frac{A_L}{2} \mu [\hat{S}(e^{jw_{L0}}) e^{j\theta_{Lk}} E(z e^{-jw_{L0}}) + \hat{S}(e^{-jw_{L0}}) e^{-j\theta_{Lk}} E(z e^{jw_{L0}})] U(z), \quad (5.18)$$

$$W_{LRk}(z) = \frac{A_R}{2} \mu [\hat{S}(e^{jw_{L0}}) e^{j\theta_{Rk}} E(z e^{-jw_{R0}}) + \hat{S}(e^{-jw_{L0}}) e^{-j\theta_{Rk}} E(z e^{jw_{R0}})] U(z), \quad (5.19)$$

where $\hat{S}(e^{jw_{L0}})$ is the estimated secondary path of the left channel at the reference frequency, μ is the step size and $U(z) = \frac{1}{z-1}$.

The partial filters' outputs which are the contribution from the k -th adaptive weight, can be expressed using z-transform as:

$$Y_{LLk}(z) = TI_{LL} + TV_{LL} = \frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(z e^{jw_{L0}}) E(z) + \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{L0}}) E(z) + \frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Lk}} U(z e^{jw_{L0}}) E(z e^{2jw_{L0}}) + \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Lk}} U(z e^{-jw_{L0}}) E(z e^{-2jw_{L0}}) \quad (5.20)$$

$$Y_{LRk}(z) = TI_{LR} + TV_{LR} = \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(z e^{jw_{R0}}) E(z) + \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{R0}}) E(z) + \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Rk}} U(z e^{jw_{R0}}) E(z e^{2jw_{R0}}) + \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Rk}} U(z e^{-jw_{R0}}) E(z e^{-2jw_{R0}}), \quad (5.21)$$

where TI is time-invariant term and TV is time-varying term [130].

Multi-reference ANC algorithm has joint output, therefore, k -th adaptive weight consists of the sum of $Y_{LRk}(z)$ and $Y_{LLk}(z)$.

$$\begin{aligned}
Y_{Lk}(z) = Y_{LLk}(z) + Y_{LRk}(z) = & \left[\frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(ze^{jw_{L0}}) E(z) + \right. \\
& \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(ze^{-jw_{L0}}) E(z) + \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(ze^{jw_{R0}}) E(z) + \\
& \left. \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(ze^{-jw_{R0}}) E(z) \right] + \\
& \left[\frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Lk}} U(ze^{jw_{L0}}) E(ze^{2jw_{L0}}) + \right. \\
& \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Lk}} U(ze^{-jw_{L0}}) E(ze^{-2jw_{L0}}) + \\
& \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Rk}} U(ze^{jw_{R0}}) E(ze^{2jw_{R0}}) + \\
& \left. \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Rk}} U(ze^{-jw_{R0}}) E(ze^{-2jw_{R0}}) \right]
\end{aligned} \quad (5.22)$$

As was shown in the previous studies [131] – [132], the high order N filter makes TI terms dominant and system more stable. Therefore, we can neglect TV terms. The final noise control signal of the left channel can be expressed as follows:

$$\begin{aligned}
Y'_L(z) = S_L(z) \sum_{k=0}^{N-1} Y_{Lk}(z) = & \frac{\mu L}{4} E(z) S_L(z) [A_L^2 \hat{S}(e^{jw_{L0}}) U(ze^{jw_{L0}}) + \\
& A_L^2 \hat{S}(e^{-jw_{L0}}) U(ze^{-jw_{L0}}) + A_R^2 \hat{S}(e^{jw_{L0}}) U(ze^{jw_{R0}}) + \\
& A_R^2 \hat{S}(e^{-jw_{L0}}) U(ze^{-jw_{R0}})]
\end{aligned} \quad (5.23)$$

where $S_L(z)$ is the z-transform of the secondary path of the left channel.

The following equations describe the transfer function of the binaural ANC algorithm. The reference signal for the left channel:

$$x_{Lk}(n) = A_L \cos(w_{L0}n + \theta_{Lk}) = \frac{A_L}{2} (e^{jw_{L0}n} e^{j\theta_{Lk}} + e^{-jw_{L0}n} e^{-j\theta_{Lk}}), \quad (5.24)$$

$$x_{L(k+N/2)}(n) = A_R \cos(w_{R0}n + \theta_{Rk}) = \frac{A_R}{2} (e^{jw_{R0}n} e^{j\theta_{Rk}} + e^{-jw_{R0}n} e^{-j\theta_{Rk}}), \quad (5.25)$$

where $N/2$ is half of the filter length.

The update of individual coefficients of two halves adaptive filter:

$$W_{Lk}(z) = \frac{A_L}{2} \mu [\hat{S}(e^{jw_{L0}}) e^{j\theta_{Lk}} E(ze^{-jw_{L0}}) + \hat{S}(e^{-jw_{L0}}) e^{-j\theta_{Lk}} E(ze^{jw_{L0}})] U(z), \quad (5.26)$$

$$W_{L(k+N/2)}(z) = \frac{A_R}{2} \mu [\hat{S}(e^{jw_{L0}}) e^{j\theta_{Rk}} E(ze^{-jw_{R0}}) + \hat{S}(e^{-jw_{L0}}) e^{-j\theta_{Rk}} E(ze^{jw_{R0}})] U(z). \quad (5.27)$$

The partial filter's output, which is the contribution from the k -th adaptive weight, can be expressed using z-transform as:

$$Y_{Lk}(z) = TI_{Lk} + TV_{Lk} = \frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(z e^{jw_{L0}}) E(z) + \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{L0}}) E(z) + \frac{A_L^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Lk}} U(z e^{jw_{L0}}) E(z e^{2jw_{L0}}) + \frac{A_L^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Lk}} U(z e^{-jw_{L0}}) E(z e^{-2jw_{L0}}) \quad (5.28)$$

$$Y_{L(k+N/2)}(z) = TI_{L(k+N/2)} + TV_{L(k+N/2)} = \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) U(z e^{jw_{R0}}) E(z) + \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{R0}}) E(z) + \frac{A_R^2}{2} \mu \hat{S}(e^{jw_{L0}}) e^{-j2\theta_{Rk}} U(z e^{jw_{R0}}) E(z e^{2jw_{R0}}) + \frac{A_R^2}{2} \mu \hat{S}(e^{-jw_{L0}}) e^{j2\theta_{Rk}} U(z e^{-jw_{R0}}) E(z e^{-2jw_{R0}}) \quad (5.29)$$

The final noise control signal of the left channel can be expressed as follows:

$$\begin{aligned} \sum_{k=0}^{N/2-1} Y_{Lk}(z) + S_L(z) \sum_{N/2}^{N-1} Y_{L(k+N/2)}(z) &= \frac{\mu L}{8} E(z) S_L(z) [A_L^2 \hat{S}(e^{jw_{L0}}) U(z e^{jw_{L0}}) + \\ &A_L^2 \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{L0}})] + \frac{\mu L}{8} E(z) S_L(z) [A_R^2 \hat{S}(e^{jw_{L0}}) U(z e^{jw_{R0}}) + \\ &A_R^2 \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{R0}})] = \frac{\mu L}{8} E(z) S_L(z) [A_L^2 \hat{S}(e^{jw_{L0}}) U(z e^{jw_{L0}}) + \\ &A_L^2 \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{L0}}) + A_R^2 \hat{S}(e^{jw_{L0}}) U(z e^{jw_{R0}}) + \\ &A_R^2 \hat{S}(e^{-jw_{L0}}) U(z e^{-jw_{R0}})] \end{aligned} \quad (5.30)$$

Compare (5.19) and (5.26), it becomes obvious that the transfer functions of multi-reference and binaural ANC algorithms are very similar. The difference is only in constant terms $\frac{\mu L}{8}$ (binaural ANC) and $\frac{\mu L}{4}$ (multi-reference ANC), which have an influence on the stability of algorithms [133]. However, these constant terms are defined by the number of filters and their total order. Figure 5.9 shows signal flow diagrams for both algorithms. Signal flow block diagrams also show the similarity between multi-reference and binaural ANC algorithms. Multi-reference ANC algorithm transfer function consists of two parts and the binaural ANC algorithm transfer function combines two parts into one. Therefore, both algorithms have different approaches but similar performance. However, the proposed binaural ANC algorithm has an advantage in terms of less required computational sources.

Figure 5.9 –a) Signal flow block diagram of multi-reference ANC algorithm (left channel only); b) Signal flow block diagram of binaural ANC algorithm (left channel only)

The proposed binaural ANC algorithm helps to improve noise reduction performance for the “worst” channel, if there is any. In other cases, the binaural ANC algorithm achieves similar results as a conventional bilateral ANC algorithm for single noise source scenarios.

5.1.4 Multiple Noise Sources Scenarios

The main focus of this chapter is on the improvement of noise reduction performance for the multiple noise sources, placed at different directions, cases. It is quite obvious that real-life environmental noise scenarios consist of multiple noises, which have different directions and SPL levels. Therefore, it is important to develop and implement a noise reduction algorithm for headphones applications, which will be efficient for real-life noise situations. Conventional bilateral ANC algorithm for headphones has high noise reduction performance for one noise source or multiple noise sources situated at the same location or the same side of the head. However, its performance decreases in the case of multiple noise sources situated at different locations. It is possible to explain by the effect of different HRTFs and head-shadow effect, which implies that the reference signal of one channel does not always provide enough information for good noise cancellation on both sides. Therefore, the bilateral ANC solution is not always efficient for the aggressive noisy environment.

In order to show the advantages of the binaural ANC algorithm and prove assumptions, it was decided to compare noise reduction performances of binaural and bilateral ANC algorithms for different noise types and noise sources locations. To validate the effectiveness of the bilateral and binaural ANC algorithm, we perform the below real-time experiments. Real-time experiments' setups are the same as was described in Section 5.1.2. The idea is to conduct experiments for different combinations of noise sources, placed at different directions, and to compare bilateral and binaural ANC algorithms noise reduction results. Three broadband noise (BBN) [134] sources are used in these experiments: 300 Hz – 600 Hz, 300 Hz – 1000 Hz and 700 Hz – 1000 Hz. All noise sources were aligned to the level of 75 dB SPL. Noise sources are situated at a distance of 1.5 m from the center of the KEMAR dummy head. Noise sources are combined for overlapping spectrums {BBN (300 Hz – 1000 Hz) and BBN(300 Hz – 600 Hz)}; and non-overlapping spectrums {BBN(700 Hz – 1000 Hz) and BBN(300 Hz – 600 Hz)}. The noise sources combinations and directions are shown in Table 5.8. It is assumed that bilateral and binaural ANC algorithms can show different behavior and results for different environmental

noise sources scenarios. Directions of the noise source, frequency contents of different noise source have an influence on noise reduction performances of both compared ANC algorithms. Real-time results for all combinations and directions are shown in Table 5.9. From Table 5.9, it is shown that the binaural ANC algorithm does not always result in the best noise reduction. There are still noise scenarios, where bilateral implementation outperforms the binaural ANC algorithm. The blue boxes in Table 5.9 highlight the binaural ANC algorithm performs better than bilateral, and the red box shows bilateral ANC algorithm performs better.

Table 5.8 Noise sources directions for real-time multiple noise source experiments [116]

Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)	Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)

Table 5.9 Real-time noise reduction results of bilateral and binaural ANC algorithms

Noise types	Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)				Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)			
ANC type	Bilateral		Binaural		Bilateral		Binaural	
Pos./Channel	L	R	L	R	L	R	L	R

0° 90°	-6.2	-3.0	-10.4	-6.2	-9.1	-8.2	-11.3	-9.5
180° 270°	-3.5	-4.6	-6.3	-8.3	-10.8	-11.6	-8.6	-9.3
90° 270°	-5.2	-3.2	-9.7	-7.6	-10.4	-8.7	-8.0	-5.1

In general, the binaural ANC is better for overlapping noise sources, however, for non-overlapping noise sources, the binaural ANC algorithm only performs better where noise sources are located at 0° (front) and 90° (the right side) positions.

- **0° and 90° directions**

Noise sources are placed in front of the dummy head and from the right side. Therefore, the right ear has an advanced position at least for the one noise source. Binaural ANC algorithm improves noise reduction performance for the “worst” left channel by 2-4 dB, and performance of the right channel by 1-3 dB for both overlapping and non-overlapping noise sources. The left channel improvement is higher because of the time advantage of the right reference signal for a noise source at 90° position, which helps to improve the left channel reduction of this noise source. Sharing of the left reference also helps to improve the right channel performance because the left reference signal has clearer information about the front noise source. Therefore, sharing of the reference and input signals is useful for this noise scenario.

- **180° and 270° directions**

The 180° (behind) and 270° (the left side) scenario is not similar to the previous directions. The head-shadow effect is more significant in this case, as a result, the frequency contents of the noise sources become a factor, which has an influence on the bilateral and binaural ANC algorithms performances. Binaural ANC algorithm is better only for overlapping noise sources. Similar to the previous scenario, improvement for the “worst” right channel, in this case, is higher (about 4 dB), and improvement for the left channel noise reduction is about 2.5 dB. However, the bilateral ANC algorithm shows better results for non-overlapping noise sources. Therefore, sharing reference and input signals with

different (non-overlapping) frequency content degrades noise reduction performance for both channels in this scenario because of the high influence of the head-shadow effect. However, the binaural ANC approach, using the left ear (with time advance information of the noise source at 270°) and doubling of reference microphones number, is better for noise sources with overlapping frequency spectrums.

- ***90° and 270° directions***

The opposite noise sources directions 90° (the right side) and 270° (the left side) scenario shows similar behavior as the previous case. Binaural ANC algorithm helps to improve noise reduction performance for overlapping noise sources. The improvements are about 4-5 dB. The left channel has better noise reduction performance because the narrower frequency band noise source is dominant at the left side. However, for non-overlapping noise sources, the bilateral ANC algorithm still performs better. The difference is about 2-3 dB. The left channel noise reduction for this scenario is higher for both ANC implementations because the lower frequency noise source is situated on the left side, and the ANC algorithm is more efficient for low-frequency noise. Thus, noise sources with overlapping frequency contents, placed at opposite sides, provide references of both channels useful for each other; but references with non-overlapping noises degrade performances of both channels. This noise direction scenario will be discussed below.

The next comparison stage is the numerical difference [135] between both ANC approaches in terms of noise reduction results. Table 5.10 shows the differences between binaural and bilateral ANC algorithms performances for all environmental noise sources scenarios. Differences are evaluated by subtraction of absolute values of bilateral ANC algorithm noise reduction results from absolute values of binaural ANC algorithm results. Thus, positive values refer to binaural ANC algorithm advantage, and negative values point to bilateral ANC algorithm advantage. Binaural ANC algorithm has an average advantage in 2-5 dB for cases where it is better. On the other hand, bilateral ANC algorithm

better cases have advantages in 2-4 dB. Thus, improvements introduced by the binaural ANC approach are slightly higher than its degradation. However, the difference is not very significant. It can be concluded that in the case of the overlapping noise spectrum, binaural always has an edge over bilateral noise control; and vice versa, for non-overlapping noise spectrum, bilateral noise control has an advantage over binaural in lateral and posterior noise sources. Two scenarios with overlapping noise sources (binaural ANC is better) and non-overlapping noise sources (bilateral ANC is better) at 90° and 270° positions are chosen for further analysis. Noise sources are placed on opposite sides of the dummy head. Therefore, this scenario can provide more complete information for comparison because each channel has its dominant noise source. The comparisons are performed in the frequency domain to evaluate noise reduction at different frequencies.

Table 5.10 Noise reduction performances' differences between binaural and bilateral ANC algorithms

Noise types	Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)		Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)	
Position/Ch.	Left (Bin-Bil)	Right (Bin-Bil)	Left (Bin-Bil)	Right (Bin-Bil)
0° 90°	4.2 dB	3.2 dB	2.2 dB	1.8 dB
180° 270°	2.8 dB	3.7 dB	-2.2 dB	-2.3 dB
90° 270°	4.5 dB	4.4 dB	-2.5 dB	-3.5 dB

Figure 5.10 shows the spectrum of the left and right channels for binaural and bilateral ANC algorithms for overlapping noise sources. The low-frequency noise reduction is poor for the bilateral ANC algorithm, especially in the right channel. However, the sharing of reference and input signals helps to improve the situation for both channels at the low-frequency range. Bilateral ANC algorithm has poor noise reduction lower than 500 Hz for both channels. The frequency range of 300 Hz – 600 Hz is an overlapping part of the presented noise sources. Therefore, both reference microphones capture this frequency range signals with different levels and time delays, which can cause stability and causality issues for bilateral ANC approach performance. By doubling of reference microphones number, the binaural ANC algorithm solves this problem.

Figure 5.10 – Bilateral ANC and binaural ANC algorithms performances for overlapping noises (90° BBN(300 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on.

Sharing of reference information provides additional information about 300 – 600 Hz overlapping ranges for both channels processing. As a result, the binaural ANC algorithm improves low-frequency noise reduction performance for both ears.

Figures 5.11 shows spectrums of the left and right channels for binaural and bilateral ANC algorithms for non-overlapping noises. The bilateral ANC approach has better noise reduction results for this scenario. Binaural ANC algorithm shows small improvements in the range around 700 Hz for the left channel because the BBN(700 Hz – 1000 Hz) is situated on the right side, which is the dominating side. Therefore, the right reference provides additional information about high-frequency noise and improves left channel reduction for this frequency range. However, additional right reference and filter input signals degrade the performance of the left channel in the range below 600 Hz, which is dominant for the left side. Therefore, the average noise reduction performance of the binaural ANC algorithm is worse for the left channel. A similar situation occurs for the right channel. The right noise source dominant frequency range 700 - 1000 Hz performance degrades in the case of the binaural ANC algorithm. Low-frequency noise reduction is also better for the bilateral ANC algorithm because 300 – 600 Hz signal is not presented from the right side.

Figure 5.11 – Bilateral ANC and binaural ANC algorithms performances for non-overlapping noises (90° BBN (700 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on.

Therefore, the time difference between signals captured by the left and right reference microphones is quite high for low-frequency noise components. Thus, sharing references and filter inputs is not efficient for non-overlapping noise sources, placed at the opposite sides.

5.1.5 Summarized Comparisons of Binaural and Bilateral ANC Approaches

According to the above results, we cannot state that the binaural ANC algorithm is always better than bilateral implementation. For single noise source comparison, the binaural ANC approach outperforms bilateral only for the cases when the noise source is placed nearer to the one ear cup and far away from another ear cup. The nearest to the noise source reference has a time advantage and it helps to improve the causality situation and performance of the opposite channel. Improvement of the “worst” channel performance is about 3 dB. However, in the cases without the “best” and the “worst” ears, binaural and bilateral ANC algorithms have similar noise reduction results. Moreover, the proposed binaural ANC algorithm was compared with the multi-reference ANC approach, proposed by J. Cheer [128]. Both algorithms show very close noise reduction results, but the proposed binaural ANC algorithm requires less computational sources. However, multiple noise sources cases are more

interesting and provide more information about binaural ANC algorithm performance. Binaural ANC algorithm improves noise reduction performance for many different environmental noise scenarios [136], especially for cases with overlapping noise sources. However, for non-overlapping noise sources, bilateral and binaural ANC algorithm performances depend on the directions and frequency contents of noise sources. Therefore, the best solution is to implement an automatic system [136], which will be able to define and select “the best” ANC approach based on the specific noise situation. The main milestone is to define the way of selecting the “best” ANC implementation based on the current noise situation. The first idea is to develop and implement an algorithm, which is able to define noise situation and predict the “best” ANC solution. Based on the real-time results, it is possible to state that the number of noise sources, frequency contents of noises and noises’ directions have an influence on the performance of different ANC approaches. It can be quite a complicated system, which is able to detect directions-of-arrival (DOA) [137], the number of noise sources [138] and to compare their frequency contents. Therefore, it is necessary to develop the simplest selection system. As was mentioned in Section 5.2, coherence between primary noise at the reference and error microphones has a strong influence on ANC algorithm performance. Higher coherence leads to higher noise reduction results [30]. Therefore, the coherence-based system can be useful and efficient in the selection of the “best” ANC implementation according to the environmental noise situation.

5.2 Combined ANC Algorithm with Bilateral and Binaural Options for Headphones

This section proposes a new combined ANC algorithm with bilateral and binaural options (CBBANC) [116]. Firstly, possible real-life environmental noise source scenarios are described, with the aim to explain that it is impossible to know in advance, which ANC implementation is more efficient. The second part of this section presents the coherence-based method of the “best” ANC algorithm selection. The proposed method is used to automatically switch between bilateral and binaural ANC implementation according to the environmental noise situation.

5.2.1 Possible Environmental Noise Scenarios

In the real world, it is quite difficult to imagine a single noise source in the open area. People mostly use headphones outside. High-level traffic noise, construction noises, human's speech can be placed in different directions and mixed with each other, it is a typical content of urban noise in the big cities. Moreover, even in closed public places, such as offices, shopping malls, cafes, surrounding noise can be annoying. Combinations of different noise sources can be more annoying than the single noise source. It is well-known that one sound source can amplify another one [139]. This phenomenon was described in Section 2.3.1. Therefore, real-life noise scenarios are not predictable and their influence on the human's hearing system can be very dangerous. It is obvious that the binaural ANC algorithm should have better noise reduction performance for most environmental noise cases. However, it is not possible to guarantee that the binaural ANC algorithm will be always better. Moreover, the environmental noise scene [140] can change fast and, also, users can change their places by moving inside/outside different areas and buildings [141].

Therefore, the right way to solve this issue is to develop and implement the ANC system, which can combine both approaches and switch [142] between them according to the noise situation. The combined ANC system should be independent of the noise situation. Moreover, it should be flexible and switch between ANC options according to the changeability of the noise situation.

5.2.2 Coherence-based Selection between Binaural and Bilateral ANC algorithms

To decide whether bilateral or binaural ANC algorithm is preferred in different environmental noise scenarios, we have to find a suitable parameter that can be used to switch between these two ANC implementations. Therefore, this section describes a switching algorithm to automatically decide on the usage of binaural or bilateral ANC implementation.

It is noted from the single-channel ANC system, strong coherence between the reference and the error microphones results in an excellent noise reduction. In Section 5.1.2, it was shown that coherence values (5.7) have an influence on the ANC algorithm performance. Therefore, the coherence-based method is chosen in this work. This observation can be extended to the error and reference microphones in both ear cups. The direct-channel coherence indicates the coherence of the error and reference microphones located at the same ear cup, while cross-channel coherence [143] refers to the coherence of reference microphone at one ear cup (e.g. L ear cup) and the error microphones at the opposite ear cup (e.g. R ear cup). By comparing the absolute (average) values of both direct-channel and cross-channel coherence across the noise bandwidth, we can devise a simple algorithm to decide on which ANC algorithm to use. Table 5.11 shows the coherence measurements for all noise sources combinations and directions.

For the 0° and 90° directions, the binaural ANC algorithm outperforms bilateral implementation for both overlapping and non-overlapping noise sources. As a result, cross-channel coherence values are higher for both cases. For the 180° and 270° directions, cross-channel coherences are higher for overlapping noise sources, where the binaural ANC approach is better, however, direct coherences are higher for non-overlapping noises, in this case, bilateral ANC algorithm has better results. The last directions of 90° and 270° have similar coherence results as for the previous direction case. As an example, in order to not overfill the thesis by similar plots, Figure 5.12 shows coherences of both channels for only overlapping noises at 90° and 270°, where the bilateral ANC algorithm is better.

Table 5.11 Direct- and cross-channel coherence measurements, based on real-time experiments [116]

Channel	Right channel		Left Channel	
Coherence type	C_{Dir}	C_{Cross}	C_{Dir}	C_{Cross}
0° and 90° (overlap noises)	0.41	0.48	0.52	0.65
0° and 90° (non-overlap noises)	0.55	0.61	0.60	0.67

180° and 270° (overlap noises)	0.48	0.63	0.38	0.43
180° and 270° (non-overlap noises)	0.71	0.68	0.65	0.63
90° and 270° (overlap noises)	0.41	0.64	0.50	0.66
90° and 270° (non-overlap noises)	0.59	0.51	0.68	0.63

Figure 5.12 - Coherences for non-overlapping noise sources noises (90° BBN (700 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents direct-channel coherence; (red) cross-channel coherence [116]

Bilateral ANC algorithm is better for this scenario and the absolute values of direct-channel coherence are higher for both channels. Cross-channel coherences significantly drop in the boundary range of two non-overlapping noises (600 – 700 Hz) for both channels. The low-frequency broadband noise source (300 - 600 Hz) is situated at the left side, direct- and cross-channel coherences of low-frequency range are quite flat and similar for the left channel because the head-shadow effect and passive attenuation of headphones are not very significant in the low-frequency range of less than 1 kHz. Higher frequency coherences are not so flat, because higher frequency broadband noise source (700 -1000 Hz) is placed at the right side and head-shadow and passive attenuation of headphones are starting to reduce the influence of binaural noise attenuation and to decrease coherences values. However, cross-channel coherence is higher for the frequency range of 700-800 Hz, which proves that the binaural ANC algorithm improves noise reduction performance

of this frequency range for the left channel (Figure 5.11). The right channel coherences are quite flat for the whole frequency range 300 – 1000 Hz because the head-shadow effect has not any influence on the high-frequency noise at the right side. However, cross-channel coherence is very low in the boundary frequency range of 600 - 800 Hz. Coherences were compared for all combinations of noise sources and positions and it was found that bilateral ANC algorithm has better noise reduction performance only in the case when:

$$C_{DirR} > C_{CrossR} \text{ AND } C_{DirL} > C_{CrossL} , \quad (5.31)$$

where direct-channel coherence is higher than cross-channel coherence. Binaural ANC approach is better when at least one cross-channel coherence (either C_{CrossR} OR C_{CrossL}) value is higher than the direct-channel coherence. Therefore, the coherence-based method can be used to control the switch to select between binaural or bilateral ANC algorithms. In Section 5.1.2, it was shown that coherence values between reference and error microphones' noise signals are used to estimate theoretical noise reduction performance for a fixed filter ANC algorithm. Therefore, this theoretical observation proves that the binaural ANC approach should have better results if cross-channel coherence is higher.

Since real-life noise sources are dynamic, but changes gradually, it is possible to implement a frame-based coherence-switch that can select the best ANC implementation. The new algorithm is expressed in the following way. At first, it is necessary to introduce a new parameter λ , as a function of coherence, which will select the type of dataset and algorithm. The first step is the estimation of ratio between C_{Dir} and C_{Cross} for both channels. It is obvious that at least one of the ratios is less than 1 for the case when the binaural ANC algorithm has better performance, but when both ratios are higher than 1 for the case when the bilateral ANC algorithm is better. Therefore, the next step is the selection of the minimum value of the two ratios.

$$\sigma = \min\left(\frac{C_{DirR}}{C_{CrossR}}, \frac{C_{DirL}}{C_{CrossL}}\right). \quad (5.32)$$

It is necessary to select between two solutions binaural or bilateral but not to

define the portions of each solution like it was done for combinations of adaptive filters in [145]. Therefore, parameter λ can be 1 or 0 and works as a switch. As was mentioned above, the σ value ranges from 0 to 1 for the situation when the binaural ANC algorithm is selected; but when σ value is higher than 1, the bilateral ANC algorithm is selected. It was decided to introduce the variable λ , which can only be either 1 or 0:

$$\lambda = \lfloor \sigma - \lfloor \sigma - 1 \rfloor \rfloor, \quad (5.33)$$

where $\lfloor \cdot \rfloor$ is the integer part of the number.

Therefore, for the case when the bilateral ANC algorithm has better performance, the value of λ is 1 and for the binaural ANC algorithm case value of λ is 0. The last stage of the new algorithm is the modification of the FxNLMS equation and filtering process equation. The new FxNLMS algorithm is expressed by the following equations:

$$\mathbf{w}_i(n+1) = \mathbf{w}_i(n) + \mu \frac{e_i(n)[\lambda \mathbf{x}_i^{'Bil}(n) + (1-\lambda) \mathbf{x}_i^{'Bin}(n)]}{\|[\lambda \mathbf{x}_i^{'Bil}(n) + (1-\lambda) \mathbf{x}_i^{'Bin}(n)]\|^2}. \quad (5.34)$$

The filtering process equations are also modified in order to select the reference signals data set according to binaural or bilateral ANC algorithms is used in the current situation case.

$$y_i(n) = \mathbf{w}_i(n) * [\lambda \mathbf{x}_i(n) + (1-\lambda) \mathbf{x}(n)]. \quad (5.35)$$

It is easy to see that for both FxNLMS and filtering process we have sum expressions in the brackets $[\lambda \mathbf{x}_i(n) + (1-\lambda) \mathbf{x}(n)]$ and $[\lambda \mathbf{x}_i^{'Bil}(n) + (1-\lambda) \mathbf{x}_i^{'Bin}(n)]$. As was mentioned above, λ can be only 1 or 0, which implies that one of the parts of the sum will be zero and it will be selected only one data set of signals according to chosen ANC implementation. Therefore, the new proposed CBBANC algorithm for headphones can automatically select and switch between bilateral or binaural ANC implementation according to the environmental noise scenario.

5.3 Analysis and Results

This section presents and describes real-time experiments' results of the proposed CBBANC algorithm. The CBBANC algorithm performance is compared with binaural and bilateral ANC algorithms, based on real-life noise reduction performance results for different environmental noise cases. The major idea is to show the advantages of the proposed CBBANC algorithm in terms of flexibility and independence on different noise scenarios. Moreover, the proposed CBBANC algorithm is compared with commercial noise cancellation headphones Bose QuietComfort 35 and Sony WH-1000XM3.

5.3.1 Approaches for Comparison

The proposed CBBANC algorithm is compared with conventional bilateral ANC implementation and earlier proposed binaural ANC algorithm. It is expected that the CBBANC algorithm should select the “best” ANC solution (bilateral or binaural) according to environmental noise scenarios. Therefore, the CBBANC algorithm should repeat or has similar noise reduction performance to the “best” of ANC variations. All comparisons are based on Matlab simulations and real-time experiments, conducted in the anechoic chamber. Experimental setups for simulation and real-time experiments are the same as were described in Section 5.1.2. Experiments are conducted for the multiple noise sources and diffuse field noise scenario. The same broadband noise sources, as for bilateral/binaural ANC algorithms comparisons, are used in these experiments.

Moreover, the proposed CBBANC algorithm is compared with commercial ANC headphones Bose QuietComfort 35 and Sony WH-1000XM3. The idea is to prove that the proposed flexible technology outperforms conventional ANC algorithm, applied in commercial headphones. It is necessary to note that there is not any possibility to embed the microphones inside the ear cups of headphones in order to capture residual noise signal and evaluate the performance of commercial headphones. Therefore, the MEMs microphones are placed inside the ears of the dummy head. The microphones' positions are shown in Appendix B.

5.3.2 Simulations/Real-time Experiments and Analysis of Results

This section is divided into two parts. The first part shows simulation results and comparisons between bilateral, binaural and CBBANC algorithms. The goal of this section is to check the CBBANC algorithm in simulations before start real-time experiments. The second part describes the real-time results of the CBBANC algorithm, which is compared to real-time results of the bilateral ANC algorithm and binaural ANC algorithm from section 5.1.3 to show the advantages of the proposed algorithm.

The proposed CBBANC algorithm automatically selects the configuration under different environmental noise scenario, based on coherence measurements. Simulations experiments are conducted to check the performance of the proposed CBBANC algorithm before the start of real-time experiments. The CBBANC algorithm should select the best implementation (bilateral or binaural) according to the environmental noise scenario. Therefore, it is expected that the CBBANC algorithm will result in the “best” results because there is not any additional processing delay in simulations. Simulations are conducted using Matlab and actual primary and secondary paths of real headphones are used. Coherences is measured every 0.5 seconds based on 1024 length frames. Table 5.12 shows simulations noise reduction results of bilateral, binaural and CBBANC algorithms.

Simulations results of bilateral and binaural ANC approaches show similar behavior as real-time results from Section 5.1.3. The proposed CBBANC algorithm selects “the best” solution for all environmental noise scenarios. The system selects the binaural ANC implementation for all noise scenarios with overlapping noise sources and 0° and 90° directions case for non-overlapping noises. As was assumed, the CBBANC algorithm repeats noise reduction results of the selected “best” ANC implementation. Simulation results prove that the proposed CBBANC algorithm is able to select “the best” ANC implementation and it is independent of noise situation. However, as was mentioned above, simulation results cannot provide a full analysis of the proposed CBBANC algorithm. Coherences measurements can produce additional time delays for real-time processing. Moreover, real-life noise

scenarios and reverberations can cause changes of coherence and the CBBANC algorithm will need to switch more often compare to simple simulation tests. Therefore, it is necessary to conduct real-time experiments to prove the CBBANC algorithm efficiency.

Table 5.12 Simulations results of bilateral, binaural and CBBANC algorithms [116]

Noise type	Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)						Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)					
ANC type	Bilateral		Binaural		CBBANC		Bilateral		Binaural		CBBANC	
Pos./Ch.	L	R	L	R	L	R	L	R	L	R	L	R
0° 90°	-12.3	-6.9	-15.5	-9.6	-15.5	-9.6	-14.4	-11.7	-16.8	-13.7	-16.8	-13.7
180° 270°	-6.1	-8.5	-8.6	-11.2	-8.6	-11.2	-15.8	-18.4	-12.9	-13.8	-15.8	-18.4
90° 270°	-10.4	-8.0	-13.1	-11.7	-13.1	-11.7	-17.1	-14.0	-14.2	-11.6	-17.1	-14.0

The CBBANC algorithm consists of two major stages: ANC procedure and coherence measurements. The ANC (bilateral or binaural) algorithm operates a non-stop sample-by-sample. As was mentioned above, coherence measurements operate every 0.5 seconds and switch the system between bilateral and binaural ANC implementations.

The processing board needs some time to measure coherence. Thus, switching cannot be realized immediately as for simulations. Therefore, it is not expected that the CBBANC algorithm will repeat the same noise reduction results as bilateral/binaural ANC algorithms for their best cases. However, the CBBANC algorithm should achieve performance close to the “best” solution and be better than the “worst” ANC algorithm. Noise reduction performances of the proposed CBBANC algorithm are shown in Table 5.13.

The CBBANC algorithm performances are slightly worse than the “best” ANC solutions from Table 5.9. However, they are significantly better than the “worst” ANC solutions. Figures 5.13 and 5.14 show noise reduction plots of three ANC approaches for all observed noise scenarios. The CBBANC algorithm

performance is closer to a binaural ANC approach for overlapping noise sources. It is obvious from Figure 5.13 that the CBBANC algorithm selects binaural implementation for overlapping noises. For non-overlapping noise sources, the CBBANC algorithm also has performance near to the “best” ANC implementation according to these noise scenarios. As the next stage of analysis, differences in noise reduction between the CBBANC algorithm and the best (bilateral or binaural) ANC algorithm are estimated for each noise scenario. Noise reduction differences are estimated by subtraction of the absolute value of CBBANC algorithm performance from the absolute value of the best ANC implementation results from Table 5.9. Table 5.14 shows the differences results.

Table 5.13 Real-time noise reduction results of CBBANC algorithms [116]

Noise type	Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)		Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)	
Pos./Ch.	Left	Right	Left	Right
0° 90°	-9.8 dB	-5.6 dB	-10.5 dB	-8.4 dB
180°270°	-6.0 dB	-7.9 dB	-10.1 dB	-11.3 dB
90° 270°	-8.9 dB	-7.2 dB	-10.0 dB	-8.0 dB

Figure 5.13 – Real-time noise reduction of 3 ANC approaches for overlapping noise sources across 3 noise sources directions, where (blue) represents Bilateral ANC on; (red) represents Binaural ANC on; (black) represents CBBANC on [116]

Figure 5.14 – Real-time noise reduction of 3 ANC approaches for non-overlapping noise sources across 3 noise sources directions, where (blue) represents Bilateral ANC on; (red) represents Binaural ANC on; (black) represents CBBANC on [116]

Table 5.14 Noise reduction differences between CBBANC and bilateral/binaural ANC algorithms [116]

Noise type	Overlap BBN(300 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)		Non-overlap BBN(700 Hz – 1000 Hz) + BBN(300 Hz – 600 Hz)	
Pos./Ch.	Left	Right	Left	Right
0° 90°	0.6 dB	0.6 dB	0.7 dB	1.0 dB
180° 270°	0.3 dB	0.4 dB	0.7 dB	0.3 dB
90° 270°	0.8 dB	0.5 dB	0.5 dB	0.7 dB

The differences between noise reduction of CBBANC and the “best” ANC implementation from Table 5.9 are about 1 dB or even less. CBBANC has very close results to the “best” solutions, which implies that it selects correct ANC implementation using the coherence-based method. As was mentioned above, the differences in noise reduction results can be caused by the time delay in switching and also, there is a possibility that the CBBANC algorithm selects different ANC implementation from frame to frame for some of the noise scenarios.

With the aim to deeper analyses CBBANC algorithm performance and behavior of the system, it was decided to investigate noise reduction performance in the frequency domain. As for the previous experiments, directions of 90° and 270° are chosen for frequency domain analysis. Spectrums of overlapping noise

sources, placed at 90° and 270° positions, for the left and right channels are presented in Figure 5.15. Binaural ANC algorithm is better for this noise scenario. Therefore, the CBBANC algorithm should select the binaural approach. Compare the spectrums of three ANC implementations, it is possible to see that CBBANC spectrums are more similar to the binaural ANC algorithm behavior. The similar behavior is observed for non-overlapping noise sources at 90° and 270° positions. Figure 5.16 shows the spectrums of all ANC approaches. After comparisons, it is possible to state that the CBBANC algorithm selects bilateral ANC implementation for this case, which has better performance.

Figure 5.15 – Bilateral ANC, binaural ANC and CBBANC algorithms performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN(300 – 600 Hz)), where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on [116]

Figure 5.16 – Bilateral ANC, binaural ANC and CBBANC algorithms performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN(300 – 600 Hz)),

where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on [116]

According to real-time results, it is possible to state that the proposed CBBANC algorithm is independent of the environmental noise scenario and it is able to automatically select the “best” (bilateral or binaural) ANC implementation, based on coherence measurements.

The next real-time experiment is conducted for diffuse field noise [145]. The idea is to compare bilateral, binaural and CBBANC algorithms for a more realistic scenario. This experiment is conducted in the reverberant meeting room. In Appendix B, the arrangement of real-time experiments for diffuse field noise is presented.

In this case, noise occurs all over the dummy head. Two noise sources are placed in the corners of the room. Both sources are broadband noise 300 -1000 Hz. Noise sources levels are aligned to 75 dB SPL at the center of the dummy head. Noise reduction results for three ANC implementations are shown in Table 5.15.

As was expected, the binaural ANC algorithm outperforms bilateral implementation. Diffuse field noise consists of many reverberations of the sound [146], which implies that there are a lot of different noise sources from many directions. Therefore, references sharing provides additional noise information for both channels, which is useful for diffuse field case. However, the binaural ANC approach improvements are not very high. It is about 2 dB. The CBBANC algorithm results are closer to the “best” binaural ANC algorithm performance. According to the coherence values from Table 5.16, it is possible to state that the CBBANC algorithm selects binaural ANC implementation for diffuse field noise scenario. Moreover, cross-channel coherences are higher than direct coherences, which proves the advantage of the binaural ANC algorithm. Figure 5.17 shows the spectrums of ANC off, bilateral, binaural and CBBANC algorithms for diffuse field case.

Table 5.15 Noise reduction results of bilateral, binaural and CBBANC algorithms for diffuse field noise [116]

ANC type/Ch.	Left	Right
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Bilateral	-4.3 dB	-5.6 dB
Binaural	-6.2 dB	-7.1 dB
CBBANC	-5.5 dB	-6.4 dB

Table 5.16 Coherence measurements for diffuse field noise scenario [116]

Ch./ Coherence type	Left	Right
Direct	0.38	0.43
Cross	0.44	0.51

Figure 5.17 – Bilateral ANC, binaural ANC, and CBBANC algorithms performances diffuse field noise, where (blue) represents ANC off; (red) represents Bilateral ANC on; (black) represents Binaural ANC on; (purple) represents CBBANC on [116]

From Figure 5.17, spectrums of the CBBANC system are more similar to the binaural ANC approach spectrums, especially for the right channel, which proves that the CBBANC algorithm selects a binaural solution for this diffuse field scenario.

5.3.3 Comparisons with Commercial ANC Headphones

This section is about comparisons between conventional bilateral ANC algorithm, implemented by us, the proposed binaural and CBBANC algorithms

and two versions of commercial ANC headphones: Sony WH-1000XM3 and Bose QuietComfort 35. The idea is to prove the advantages of the proposed binaural and CBBANC algorithms for multiple and real-life noise sources scenarios. In Section 2, spectrums of broadband noise for ANC on/off for both commercial headphones, Sony WH-1000XM3 and Bose QuietComfort 35, are shown. These plots are taken from the Rtings.com website. However, it is not enough for full comparison with the proposed ANC algorithms. Therefore, it was decided to conduct real-time experiments for both commercial ANC headphones using the same experimental arrangements as for bilateral, binaural and CBBANC experiments. Noise reduction performances of both commercial ANC headphones, bilateral, binaural and CBBANC algorithms are shown in Figures 5.18 and 5.19. In comparison of performances of Sony WH-1000XM3 and Bose QuietComfort 35, both commercial noise reduction headphones have similar noise reduction results. However, as was possible to see from Figures 2.7 and 2.8, Sony WH-1000XM3 has slightly better average noise reduction performance.

Figure 5.18 – Bilateral ANC, binaural ANC, CBBANC algorithms and commercial Bose and Sony headphones performances for overlapping noise sources

Figure 5.19 – Bilateral ANC, binaural ANC, CBBANC algorithms and commercial Bose and Sony headphones performances for non-overlapping noise sources

- ***Bilateral ANC algorithm better cases (non-overlapping noise sources at the directions of 180° - 270° and 90° - 270°)***

Firstly, the cases, where bilateral ANC algorithm is better, are analyzed and discussed. As was shown above, bilateral ANC algorithm has better results for non-overlapping noise sources at the directions of 180° - 270° and 90° - 270°. For non-overlapping noises from 180° and 270° directions, the bilateral ANC algorithm has -10.8 dB reduction for the left channel and -11.6 dB for the right channel. The CBBANC algorithm selects bilateral ANC implementation as the best in this case and its noise reduction results are similar to the bilateral ANC approach: -10.1 dB for the left channel and -11.3 dB for the right channel. Commercial ANC headphones show very similar performance for this noise situation. Bose QuietComfort 35 has a noise reduction performance of -11.5 dB for the left channel and -12.1 dB for the right channel. Sony WH-1000XM3 noise reduction results are -10.8 dB for the left channel and -12.0 dB for the left channel. For 90° and 270° directions, behaviors of all compared ANC variations are similar to the previous noise scenario. Bilateral ANC algorithm has noise reduction results of -10.4 dB for the left channel and -8.7 dB for the right channel. The CBBANC algorithm has very close results to the bilateral ANC implementation: -10 dB – the left channel and -8. dB – the right channel. Both commercial ANC headphones have slightly better results compared to bilateral

and CBBANC implementations. However, the highest noise reduction difference is about 1 dB, which implies that commercial ANC headphones results are quite similar to the conventional bilateral ANC implementation.

- ***Binaural ANC algorithm better cases (overlapping noise sources at all investigated directions and non-overlapping noise sources at 0° - 90° direction)***

Binaural ANC algorithm outperforms the conventional bilateral ANC approach for overlapping noise sources from all investigated directions. The CBBANC algorithm has similar results as the binaural ANC algorithm for these cases. For overlapping noises at 0° and 90°, the binaural ANC algorithm has a noise reduction of -10.4 dB for the left channel and -6.2 dB for the right channel. The CBBANC algorithm results are -9.8 dB for the left channel and -5.6 dB for the right channel. Commercial ANC headphones show similar to binaural and CBBANC algorithm noise reduction results for the “best” right channel. However, the “worst” channel noise reduction results are poorer for both commercial ANC headphones. It is possible to explain by the fact that commercial ANC headphones use conventional fixed filter ANC technique, and the “best” side reference signal is not used for the “worst” channel processing. Binaural ANC approach has an advantage, compare to the commercial ANC headphones, in about 2 – 3 dB for the “worst” channel. The CBBANC algorithm is better in about 1.5 – 2.5 dB in this case. However, it is necessary to note that commercial ANC headphones are slightly better than the bilateral ANC algorithm, implemented by us, for the “worst” channel.

The algorithms’ behaviors are similar for overlapping noises at 180° and 270° directions. The proposed binaural ANC algorithm improves noise reduction performance of the “worst” right channel. The CBBANC algorithm selects binaural ANC implementation as the best for this case. Binaural ANC algorithm results are -6.3 dB for the left channel and -8.3 dB for the right channel. The CBBANC algorithm results are quite similar: -6 dB – left channel and -7.9 dB – right channel. Commercial ANC headphones have close noise reduction results for the “best” left channel. However, noise reduction performances of commercial ANC headphones drop for the “worst” right channel. The proposed

binaural and CBBANC algorithms outperform commercial headphones for the “worst” channel in about 1.5 – 2.5 dB.

As was discussed above, environmental noise sources scenario of overlapping noise sources, placed at 90° and 270° directions, has not any the “worst” and the “best” channels. Binaural ANC algorithm noise reduction results are -9.7 dB for the left channel and -7.6 dB for the right channel. The CBBANC algorithm results are -8.9 dB and -7.2 dB. Commercial ANC headphones have worse noise reduction results for this environmental noise sources scenario compare to binaural and CBBANC algorithms. Binaural ANC algorithm noise reduction advantage is about 2 – 2.5 dB and the CBBANC algorithm is better than commercial ANC headphones results by about 1.5 - 2.5 dB.

Only one scenario of non-overlapping noise sources, 0° and 90° direction, shows that the binaural ANC algorithm is more preferable in this case. Binaural ANC algorithm noise reduction performances are -11.3 dB for the left channel and -9.5 dB for the right channel. As was shown in Section 5.3.2, the CBBANC algorithm also selects a binaural ANC solution for this noise sources case. The CBBANC algorithm noise reduction results are -10.5 for the left channel and -9.5 dB for the right channel. According to Figure 5.18, it is possible to state that the proposed binaural and CBBANC algorithms are still better than commercial ANC headphones. However, the advantages of binaural and CBBANC algorithms are not so significant for this noise sources scenario. The improvements are about 1 - 1.5 dB.

According to the results of the comparisons, it is possible to state that commercial ANC headphones have performances closer to the conventional bilateral ANC algorithm. In the cases, where the bilateral ANC algorithm is better, noise reduction results of the proposed CBBANC algorithm and commercial ANC headphones are similar, even commercial headphones are slightly better. However, in the case where the binaural ANC algorithm is doing a better job, the proposed CBBANC algorithm outperforms commercial ANC headphones. Especially, it is easy to observe for the scenarios, where the “worst” and the “best” channels are presented. Binaural and CBBANC algorithms significantly improve noise reduction performance of the “worst”

channel, the average improvement is about 2 dB.

To complete analysis and comparisons between the proposed ANC algorithms and commercial ANC headphones, spectrum analysis for 90° and 270° directions is conducted, as was done for bilateral and binaural ANC algorithms comparisons. It is obvious that passive attenuation of Beyerdynamic – Custom One Plus headphones (used by us), Sony WH-1000XM3 and Bose QuietComfort 35 are quite different. Therefore, the level and shape of primary noises are also different. Thus, separate plots are used for bilateral/binaural/CBBANC algorithms (Beyerdynamic – Custom One Plus headphones), for Sony WH-1000XM3 and Bose QuietComfort 35. Figures 5.20 and 5.21 show spectrums of commercial headphones and bilateral/binaural and CBBANC algorithms for overlapping noise sources at 90° and 270° directions of the left channel and the right channel, respectively. Among all tested headphones, Bose QuietComfort 35 has the best passive attenuation results. However, the differences in passive attenuation are not too high for all three headphones. Commercial ANC headphones show results similar to the bilateral ANC algorithm performance. However, the binaural ANC algorithm is better for this environmental noise sources scenario. It is easy to see from spectrums that binaural and CBBANC algorithms have better noise reduction performances compare to both commercial ANC headphones results. Figure 5.22 and 5.23 show spectrums of commercial headphones and bilateral/binaural and CBBANC algorithm for non-overlapping noise sources at 90° and 270° directions of the left channel and the right channel, respectively. Bilateral ANC algorithm shows better noise reduction performance for this environmental noise scenario. Commercial ANC headphones have slightly better noise reduction results compare to the bilateral ANC algorithm implemented by us. However, the difference is not significantly high, not more than 1 – 1.5 dB. These results prove the previous observation that commercial ANC headphones' performances are closer to the bilateral ANC algorithm results. Real-time experiments and comparisons with commercial ANC headphones Sony WH-1000XM3 and Bose QuietComfort 35 show that the proposed binaural and CBBANC algorithms are more efficient than commercial headphones for the environmental noise case, where binaural ANC algorithm has advantages.

Therefore, sharing the references and artificial increasing of reference microphones number helps to improve commercial ANC headphones' performance for most real-life environmental noise sources scenarios. The proposed binaural and CBBANC techniques can be embedded in commercial headphones without a high increase in the headphones' price. No additional hardware is required. The major part of the proposed algorithm is realized in the digital domain and requires only computational sources.

Figure 5.20 – Performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the left channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on

Figure 5.21 – Performances for overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the right channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on

Figure 5.22 – Performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the left channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on

Figure 5.23 – Performances for non-overlapping noises (90° BBN (300 – 1000 Hz) and 270° BBN (300 – 600 Hz)) of the right channel, a) Sony WH-1000XM3 where (blue) represents ANC off and (red) represents ANC on; b) Bose QuietComfort 35 where (blue) represents ANC off and (red) represents ANC on; c) Bilateral/binaural/CBBANC where (blue) represents ANC off, (red) represents bilateral ANC on, (black) represents Binaural ANC on and (purple) represents CBBANC on

5.4 Conclusions

This chapter first proposed a binaural ANC algorithm and evaluated its performance over single and multiple noise sources positioned in different directions. It was found to have an average noise reduction improvement of about 3-5 dB for multiple noise sources distributed over different locations and for diffuse field noise. However, bilateral ANC algorithm can perform better than the binaural ANC algorithm (by 1-2 dB) where the direct coherence between primary and error signals at each ear cup is higher than the cross-channel coherence between the left/right primary signals and the right/left error signals, which led to a formulation of a new CBBANC algorithm. This latter algorithm

automatically selects and switches between binaural and bilateral ANC algorithms according to the direct and cross-channel coherence measurements, which are highly affected by the environmental noise scenarios. The proposed CBBANC algorithm was tested in the real-time experiments for multiple noise sources from different directions and diffuse noise field case. The proposed CBBANC system showed that it is able to select the best binaural or bilateral implementation to handle different noise environments and repeat the noise reduction performance of the best ANC implementation. However, coherence computation takes some processing time. Therefore, the CBBANC algorithm is not able to fully repeat the result of the “best” ANC implementation. Nevertheless, CBBANC algorithm results are much closer to the “best” solution. Moreover, the CBBANC algorithm was compared with the noise reduction performance of two types of commercial ANC headphones: Sony WH-1000XM3 and Bose QuietComfort 35. The CBBANC algorithm based ANC headphones outperforms both commercial ANC headphones in the environmental noise cases, where the binaural ANC algorithm is the “best” solution. Commercial ANC headphones have results quite similar to the bilateral ANC implementation.

Chapter 6

Binaural ANC Algorithm for Hearing Aids

This chapter presents a new application of the proposed binaural ANC algorithm. Hearing aids [147] have some functions similar to headphones. Hearing aids and headphones are both hearing devices, which are placed in or around the ear and directly influence the sound received at the eardrum. Therefore, it was decided to extend the application area of the proposed binaural ANC algorithm. This part of the thesis is developed and implemented with collaboration with Sivantos Pte. Ltd., Singapore. All experiments and results, discussed in this chapter, are based on the real hearing aids prototypes.

6.1 Introduction in Hearing Aids and Hearing Aids Environmental Noise Problems

Hearing aids (HAs) are medical devices, which help hearing-impaired persons to communicate with each other. However, HAs suffer from the unwanted environmental noise, which can leak into the ear canal or be amplified together with the target sounds. As was mentioned in Chapter 2, the optimal Wiener filter and spectral subtraction are commonly used noise reduction algorithms for HAs. These approaches assume that short-time [148] noise features do not vary significantly with time. The ANC algorithm was integrated into the traditional HAs noise reduction algorithms to reduce leakage effects [149]. Conventionally, the bilateral ANC approach is used for HAs applications.

6.1.1 Types of Hearing Aids

Hearing aids are widely presented in the commercial market nowadays. It is a connection between hearing-impaired persons and the real world. HAs are classified into 4 general types [150].

1. Behind-the-ear (BTE) [151] HAs are situated behind the human's ear and send sound through the flexible tubing connector to the ear canal. There are some different sub-types of BTE HAs. The most popular are "receiver in the ear", "receiver in the canal" and "loudspeaker in the ear". Most of the BTE HAs are equipped with the soft dome, which is connected to a tube. This approach is known as an open ear fitting. Users can feel sounds more natural and realistic in this case. However, open ear fitting is not useful for all levels of hearing loss. It can be used only for mild or moderate levels. Figure 6.1 - a) shows the typical BTE HAs.

2. The second type is in-the-ear (ITE) HAs [152]. These HAs have their working parts in the earmold. Therefore, the whole HAs unit is placed inside the ear. ITE HAs have different sizes and power. However, all ITE HAs can be seen in the ear from the side. ITE HAs are the most popular nowadays. However, they have some disadvantages too. If a person has a small ear canal, severe hearing loss or ear infections, BTE HAs are not useful. Figure 6.1 – b) shows BTE HAs.

3. Completely-in-the-canal (CIC) [153] HAs are less visible and fit inside the ear canal. CIC HAs have a smaller size compared to the ITE HAs. They have a hearing loop setting [154] because of their sizes. Therefore, it is not suitable for everyone. Figure 6.1 – c) shows CIC HAs.

4. The newest type is invisible-in-the-canal (IIC) [155] HAs. They are very small and fit deeply inside the ear canal. It can be removed by the professional audiologist only. Most of these HAs are selected privately with the help of an audiologist. Selection depends on the level of hearing loss, size of the ear canal and even the user's lifestyle. Figure 6.1 – d) shows IIC HAs.

Figure 6.1 – a) Behind-the-ear hearing aids; b) In the ear hearing aids; c) Completely-in-the-canal hearing aids; d) Invisible-in-the-ear hearing aid [156]

In this thesis, we will focus on the ITE HAs. ITE HAs are widely used nowadays. Construction of the ITE HAs is similar to the earphones. Moreover, the sizes of the inner and outer parts of the ITE HAs unit allow to place the internal and external microphones for noise reduction needs.

6.1.2 Environmental Noise Problems and HAs Noise Reduction Approaches

Environmental noise influences the sound quality of HAs. Therefore, several noise reduction approaches are integrated into modern HAs. The goal of the noise reduction algorithms is to reduce unwanted noise and to enhance the intelligibility of the target sound, for example, speech. Environmental noise leaks into the ear canal and mixes with the target sound. Furthermore, noise can be captured by the HAs' microphone, amplified and sent to the ear canal by the HAs processor.

Commonly, the optimal Wiener filter and spectral subtraction approaches are applied in HAs. Both approaches are not very sensitive to the fast-changing noise situation. Moreover, HAs' noise reduction methods reduce outside noise, which was captured by the HAs' microphone, and do not consider noise, which leaks into the ear canal. In subsection 2.3.2, the binaural noise reduction algorithm for the hearing aids was described. These algorithms are based on the optimal Wiener filter with modifications according to the binaural nature of the hearing system and the advantages of binaural techniques. The proposed binaural algorithms improve noise reduction performance, however, it is still the same problems as for conventional optimal Wiener filter technique. In [149], a conventional ANC algorithm was applied for HAs as an additional noise reduction approach, which is applied to reduce leakage environmental noise. The conventional Wiener filter noise reduction algorithm is applied as a main noise reduction approach, and the ANC algorithm focuses on the effects of noise leakage through the fitting.

In this thesis, a new binaural ANC algorithm is extended according to the HAs needs. Firstly, different ITE HAs configurations are developed and investigated to get the best configuration for the ANC algorithm. Hearing aids have compact

size compare to the closed-back headphones. Therefore, the distance between the reference and error microphones decreases, which can cause causality issues. These small-size configurations influence ANC physical limitations [157]. In this thesis, the ANC algorithm is used as the main algorithm for HAs to reduce the leakage environmental noise. With the aim to improve noise reduction and solve possible causality issues, which can be caused by the HAs ANC physical limits, the binaural ANC algorithm is applied to HAs application and compared with conventional bilateral ANC algorithm.

6.2 Binaural ANC Algorithm for Hearing Aids

This section discussed the application of the binaural ANC algorithm to HAs. The first part is about the development and selection of the most suitable ITE HAs configuration [158], which can allow the “best” ANC results. The second part is based on the discussion of the assumed advantages and issues of the binaural ANC algorithm for HAs applications.

6.2.1 ITE Hearing Aids Configurations

In this section, several possible HAs configurations are presented and investigated according to the ANC algorithm needs. Hearing aids prototypes are made on the base of the real ITE HAs produced by Sivantos Pte. Ltd [159]. The HAs prototypes are equipped by two microphones (error and reference) per channel. Hearing aids are placed on the KEMAR dummy head. The ANC algorithms are implemented using the same setups as for headphones implementation: Texas Instruments TMS320C6713DSK development board with additional two daughter boards DSK6713IF-A and MSPAMP800, which provide adjustment of gains for error and reference microphones and secondary sources independently. Firstly, real-time bilateral ANC experiments are conducted to define the “best” configuration of HAs. Two HAs configurations are examined. Both HAs configuration are shown in Appendix B.

The reference microphone is situated at the outside part of the HAs, the error

microphone is placed after emitter to fit into the ear canal and control noise inside the human ear. The distance between the reference and error microphones is about 2 cm. With the aim to investigate how good is this configuration #1 for the ANC algorithm, a simple real-time experiment is conducted for one (left) channel. Four single noise sources (200 Hz tone, 300 Hz tone, 500 Hz tone, and 300-1000 Hz bandlimited broadband noise) are placed in front of dummy head at the distance of 60 cm from the center of the head. The real-time noise reduction results of conventional bilateral ANC algorithm for configuration #1 are shown in Table 6.1. According to real-time results, there is not any noise reduction for the lowest frequency tone of 200 Hz. Noise reduction performances are satisfied for all other noise sources, about 15-20 dB for tonal noises and about 8 dB for broadband noise. However, it is still necessary to solve the low-frequency issue. Figure 6.2 shows the bandlimited white noise spectrum for ANC on/off cases to investigate if there are any problems with low-frequencies reduction. Noise reduction starts from 600 Hz, however, the BBN range is 300 – 1000 Hz. Therefore, configuration #1 of ITE HAs cannot satisfy ANC needs.

Table 6.1 Bilateral ANC noise reduction results for the ITE HAs configuration #1

Noise Type	200 Hz	300 Hz	500 Hz	BBN
Noise Reduction	N/A	-19.6 dB	-17.2 dB	-7.7 dB

Figure 6.2 – Spectrums of bilateral ANC off/on for BBN (1st ITE HAs configuration)

The distance between the reference and error microphones is small and the ear canal is open for configuration #1, which causes causality issues for low-frequency noise. To solve causality problems, it requires to get the primary path group delay higher than the secondary path group delay for all frequencies. It was decided to increase group delay of the primary path by adding a double rubber dome [160] to block the ear canal. The error microphone is threaded through a tiny hole in the rubber dome to be placed deep inside the ear canal. The double rubber dome helps to close the ear canal together with the error microphone and secondary source. Moreover, the rubber dome fixes the position of HAs inside the ear. These features should increase the group delay of the primary path and make the secondary path more stable [161]. Measurements show that a double rubber dome increases the primary path group delay from 0.2 ms to 0.4 ms on average. Table 6.2 presents noise reduction results for the same noise scenarios as was done for the configuration #1. Configuration #2 improves noise reduction performance for all noise scenarios.

Noise reduction of the lowest 200 Hz tonal noise is about -6 dB. It is better than for the configuration #1. However, compared to the performance of other noise sources, 200 Hz tone reduction is still not high. Figure 6.3 shows the spectrums of the broadband noise when the ANC algorithm is turned on/off to check improvements in the low-frequency range performance for the broadband noise source. Noise reduction starts from frequencies of 350-400 Hz, which implies that the configuration #2 improves causality requirements and noise reduction of the low-frequency noises. Moreover, additional double rubber dome increases passive attenuation, the level of the primary noise (ANC off case) is lower compared to the configuration's #1 spectrum.

Table 6.2 Bilateral ANC noise reduction results for the ITE HAs configuration #2

Noise Type	200 Hz	300 Hz	500 Hz	BBN
Noise Reduction	-5.5 dB	-19.6 dB	-17.2 dB	-7.7 dB

However, noise reduction performances for 200 HZ tone and broadband noise are not high. It is still necessary to improve low-frequency noise reduction performance for the HAs ANC system. Therefore, it was decided to apply the proposed binaural feedforward ANC algorithm to improve the average noise reduction performance of the HAs ANC system.

Figure 6.3 – Spectrums of bilateral ANC algorithm off/on for BBN (2nd ITE HAs configuration)

6.2.2 Considerations of Binaural ANC Algorithm for Hearing Aids Applications

The same binaural ANC algorithm, which was developed and implemented for headphones in Chapter 5, is applied for HAs. Binaural ANC setups are also similar to headphones case, two adaptive filters (1 per channel) of 400 taps order. The major issue of the HAs ANC system is the causality requirements. The HAs are very compact devices and the distance between reference and error microphones is about 2 cm. Moreover, HAs are not able to cover ear as closed-back headphones. Therefore, the group delay of the acoustic primary path cannot be the same as for headphones. Based on these observations, the main aim of the binaural ANC algorithm is to improve the causality situation. As was shown in Section 5.1.3, the binaural ANC algorithm helps to solve causality issues, especially for the low-frequency noises. Binaural ANC algorithm improves causality situations in the cases when the “best” and the “worst” ears

are presented. These situations depend on the noise sources directions, which implies that noise source is placed near the one ear (the “best”) and sound reaches this ear faster than the other one, without any head-shadow effect. In these cases, sharing of the references is useful for the “worst” ear because the “best” ear’s reference has a significant time advantage compared to the desired signal at the error microphone of the “worst” channel. Moreover, the binaural ANC algorithm is useful for multiple noise sources scenarios, which was evaluated for headphones. The ANC algorithm for HAs should be efficient for the aggressive noise environment with multiple noise sources from different directions.

The global aim is to prove that the binaural ANC algorithm is efficient for different multimedia and medical devices [162], which require two channels of noise reduction processing. The idea is to show that the proposed binaural ANC algorithm can be applied not only for headphones, but it has a wider range of applications.

6.3 Results and Discussions of Binaural ANC Algorithm for Hearing Aids

The real-time experiments are conducted to compare the conventional ITE HAs ANC approach with the proposed binaural ITE HAs ANC algorithm. Both algorithms are tested using the 2nd HAs configuration. The single-noise source and multiple-noise sources scenarios are evaluated to prove the efficiency of the proposed binaural ANC approach.

6.3.1 Single Noise Source Scenarios

Firstly, the real-time experiments are conducted for the single-noise source to show that the binaural ANC algorithm helps to solve the causality issue. The experiments are conducted in the reverberant laboratory room. Three tonal

noise sources: 200 Hz, 300 Hz, and 500 Hz, and broadband bandlimited noise (300 – 1000 Hz) are used for the single-noise source experiments. Two directions of a noise source (0° front position and 90° right-side position) are used to compare bilateral and binaural ANC algorithms. The noise sources are placed at a distance of 60 cm from the center of the dummy head. Table 6.3 shows the real-time results of both channels for 0° position. Noise reduction performances of binaural ANC and bilateral ANC algorithms are similar for 0° noise source direction. The noise source is situated in the frontal position. Therefore, noise reaches both ears almost at the same time. There is not any time advantage between channels and the causality situation is similar for both channels. Table 6.4 shows noise reduction results for the same noise sources but placed at 90° direction (the right side). The noise sounds reach the right reference microphone faster than the left reference microphone. Moreover, noise can reach the left error microphone first before the left reference microphone, which causes a causality issue for the left channel. The binaural ANC algorithm helps to improve the performance of the “worst” left channel for 90° noise sources direction. The right reference signal provides additional noise information for the left channel processing. The right reference signal has a time advantage compared to the left error signal. Therefore, the right reference helps to improve the causality situation for the left channel, which is shown in Figure 6.4, where BBN spectrums for binaural ANC on/off of the left channel are presented. It is obvious that noise reduction for BBN starts from 300 Hz for the “worst” left channel to compare to the bilateral ANC algorithm results from Figure 6.3. Therefore, the 2nd configuration of ITE HAs and the binaural ANC algorithm helps to improve the causality situation and to achieve noise reduction for the low-frequency range.

Table 6.3 Real-time noise reduction result of bilateral and binaural ANC for HAs for single noise source at 0° direction

ANC Type Noise type/Ch.	Binaural ANC		Bilateral ANC	
	Left	Right	Left	Right
200 Hz	-6.4 dB	-7.1 dB	-5.5 dB	-6.9 dB
300 Hz	-25.4 dB	-24.8 dB	-23.9 dB	-24.6 dB
500 Hz	-23.0 dB	-23.8 dB	-23.0 dB	-24.0 dB
BBN	-8.5 dB	-8.9 dB	-8.7 dB	-9.1 dB

Table 6.4 Real-time noise reduction result of bilateral and binaural ANC for HAs for single noise source at 90° direction

ANC Type	Binaural ANC		Bilateral ANC	
Noise type/Ch.	Left	Right	Left	Right
200 Hz	-8.3 dB	-12.9 dB	-4.1 dB	-12.5 dB
300 Hz	-22.6 dB	-21.8 dB	-19.2 dB	-20.9 dB
500 Hz	-21.2 dB	-24.0 dB	-19.0 dB	-24.6 dB
BBN	-7.2 dB	-7.7 dB	-4.1 dB	-7.5 dB

Figure 6.4 – Spectrums of binaural ANC off/on for BBN (the left channel; 2nd ITE HAs configuration)

Moreover, from Table 6.4, it becomes obvious that the binaural ANC algorithm improves the average noise reduction for the “worst” channel. Improvement for a single noise source is about 3-4 dB. It is necessary to note that reference and filter input signals of the “worst” channel are used for the “best” channel processing according to the idea of the proposed binaural ANC algorithm. However, the noise reduction of the “best” channel is similar for bilateral and binaural ANC algorithms. The “worst” channel noise information slightly degrades noise reduction performance of the “best” channel. However, degradations are not significant, not exceed 1 dB. Therefore, the binaural ANC algorithm is useful for single noise sources scenarios for HAs applications.

6.3.2 Multiple Noise Sources Scenarios

In Chapter 5, the binaural ANC algorithm showed an advantage in noise reduction performance for multiple noise sources in headphones applications.

Therefore, multiple noise sources experiments are conducted to investigate binaural ANC algorithm performance for HAs. The HAs binaural ANC algorithm is still ongoing research. The experiments are conducted in the reverberant room. The only noise sources combination and one combination of directions are investigated. The bandlimited broadband noise (300 -1000 Hz), placed at 0°, and 500 Hz tonal noise, placed at 90°, are used for this experiment. Based on the experimental setup, one noise source is placed in front of the dummy head and another – from the right side, both at the distance of 60 cm from the center of the dummy head. Thus, there is a situation with the “worst” and the “best” channels. The BBN is placed at the frontal position and reaches both ears at the same time. The tonal noise is placed at the right side of the dummy head, which makes the left channel causality situation worse. Table 6.5 shows the multiple noise source scenario results.

The proposed binaural ANC algorithm improves noise reduction performance for multiple noise sources for both channels. The “worst” left channel improvement is about 3.5 dB and the right channel improvement is about 2 dB. The tonal noise source is situated on the right side, thus, the right reference signal helps to improve the left channel performance mostly for the tonal noise. Figure 6.5 shows the spectrums of the left channel for both ANC algorithms. It is obvious that the binaural ANC algorithm improves noise reduction in the frequency range around 500 Hz. At the same time, the left reference signal has bandlimited broadband noise, as dominant because it is placed at the front and less corrupted by tonal noise compare to the right reference signal. Therefore, the right channel performance is improved by using the left reference signal too. Focusing on each noise source separately, bilateral ANC algorithm attenuates tonal noise in about 40 dB and BBN in about 8 – 11 dB, binaural ANC algorithm results are about 55 dB for tonal noise and about 7 – 10 dB for the BBN for the left channel. The right channel comparison is the following: bilateral ANC algorithm reduces the tonal noise by 50 dB and BBN by about 6 – 10 dB; binaural ANC algorithm reduces the tonal noise by about 48 dB and BBN by 8 – 12 dB.

Table 6.5 Real-time noise reduction result of bilateral and binaural ANC for HAs for multiple noise sources

ANC Type	Binaural ANC		Bilateral ANC	
Channel	Left	Right	Left	Right
Reduction	-13.8 dB	-15.0 dB	-10.2 dB	-13.4 dB

Figure 6.5 – Multiple noises spectrums of binaural ANC on/off for the left channel;
Multiple noises spectrums of bilateral ANC on/off for the left channel;

These results also prove the previous observation about the efficiency of the binaural ANC algorithm for multiple noise sources from different directions. It is possible to state that the proposed binaural ANC algorithm for HAs applications improves noise reduction performance for different noise sources scenarios.

6.4 Occlusion Canceller for Hearing Aids

This section describes the occlusion effect [163] issues for ITE HAs. The occlusion effect solution is proposed based on the modified feedback ANC algorithm. The experimental results show the efficiency of the adaptive occlusion effect canceller.

6.4.1 Occlusion Effect

As was mentioned in the previous section, a double rubber dome was added to improve the causality situation. However, a double rubber dome completely

covers the ear canal, which causes the occlusion effect. The perception of the own voice is a combination of two sounds, the outer air-conducted sound, and the inner bone-conducted sound. This fact explains the difference in perception of the own and recorded voice. In HAs applications, outer components are attenuated by the earmold, especially the high-frequency part. Therefore, low-frequency (200 Hz - 500 Hz) components of the inner sound are amplified inside the ear canal. Sometimes this amplification can reach up to 30 dB. The occlusion effect can be estimated as a frequency-dependent ratio:

$$OE(f) = \frac{|D_{occl}(f)|}{|D_{open}(f)|}, \quad (6.1)$$

where $D_{occl}(f)$ is the voice signal at the eardrum with occlusion, $D_{open}(f)$ is the voice signal at the eardrum with the open ear canal.

However, it is not possible to reproduce exactly the same voice sound with and without occlusion. Therefore, for practical applications, the occlusion effect is estimated as the ratio between the voice signal at the external reference microphone $X(f)$ and voice signal at the eardrum (error microphone) with occlusion in the frequency domain.

$$OE(f) = \frac{|D_{occl}(f)|}{|X(f)|}. \quad (6.2)$$

6.4.2 Adaptive Algorithm for Occlusion Effect Cancellation

The occlusion effect issue is not new for HAs applications. There are several techniques and algorithms [164] – [165] were proposed to reduce this effect. The idea is to find and implement the most suitable solution, which can be easily integrated into the proposed binaural ANC algorithm. Therefore, it was decided to apply the technique based on the modified feedback ANC implementation [165]. The adaptive occlusion effect canceller focuses on the low-frequency sounds, up to 500 Hz. The block diagram of the adaptive occlusion effect canceller is shown in Figure 6.6.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{e(n)\mathbf{q}'(n)}{\|\mathbf{q}'(n)\|^2}. \quad (6.5)$$

The adaptive occlusion effect canceller is easily integrated into the proposed binaural ANC algorithm. It is obvious that the own voice is perceived similar by both ears, and the left and right reference microphones also capture similar voice components. Moreover, the inner own voice signals, which propagate through the bones, are very similar. Therefore, it is not necessary to apply the binaural technique for the occlusion effect canceller. Two independent adaptive occlusion effect canceller, for one channel each, is found to be a suitable solution. The simplified block diagram of the full noise reduction system for HAs for the one channel is shown in Figure 6.7. The acoustic domain sound $x(t)$ consists of the environmental noise signal and the own voice signal. The joint noise control signal is the sum of the binaural ANC algorithm output and adaptive occlusion effect canceller output:

$$y(n) = y_{BA}(n) + y_{OC}(n), \quad (6.6)$$

where $y_{BA}(n)$ is the noise control signal of the binaural ANC algorithm and $y_{OC}(n)$ occlusion effect control signal of the occlusion canceller.

6.4.3 Results of the Adaptive Occlusion Effect Canceller

This sub-section presents the occlusion effect attenuation results of the adaptive occlusion effect canceller. The current configuration of the ITE HAs with the binaural ANC option is not applicable for the real person because the internal error microphone is quite big and very uncomfortable inside the ear canal. Therefore, the occlusion effect is simulated using the recording of the vowel sound /u:/ as voice signal captured by the reference microphone and its low-frequency equalized version as the inner voice signal, passed through bones. The voice signal at the eardrum with occlusion is defined as follows:

$$d_{occl}(n) = \left[\sum_{j=0}^{N-1} p_j(n)z(n-j) \right] + r(n), \quad (6.7)$$

where $p(n)$ is the primary path impulse response and $r(n)$ is the inner voice signal, captured by the error microphone.

Figure 6.7 – Block diagram of the integrated binaural ANC algorithm and adaptive occlusion effect canceller for HAs applications (for the right channel)

Figure 6.8 shows the results of the adaptive occlusion effect canceller, compared to one without occlusion effect cancellation. Figure 6.8 presents occlusion effect with and without adaptive occlusion effect canceller. The occlusion effect is estimated by equation (6.2).

Figure 6.8 – Occlusion effect without adaptive occlusion effect canceller (blue line) and with adaptive occlusion effect canceller (red line)

The narrowband low-frequency sounds are the main target of the adaptive occlusion effect canceller. Therefore, the order of the adaptive filter is less than for binaural ANC algorithms. The adaptive filter of the 256 taps filter's order is used in this experiment. The target frequency range of the occlusion effect for the vowel sound /u:/ is up to 400 Hz. Figure 6.8 proves the efficiency of the adaptive occlusion effect canceller for the target frequency range. The average occlusion effect attenuation is about -15 dB. Therefore, the adaptive occlusion effect canceller helps to solve the occlusion effect issue, caused by the double rubber dome for HAs noise reduction applications.

6.5 Conclusions

This chapter's contributions are divided into two parts. Firstly, the most suitable configuration of the ITE HAs prototype is proposed according to the ANC algorithm needs. The proposed configuration helps to improve the causality situation and makes low-frequency noise reduction possible. The idea is to use a double rubber dome to cover the ear canal and to place an error microphone after dome inside the canal. This configuration increases the group delay of the primary path by 0.2 – 0.4 ms. However, there is still a causality issue for the low-frequency noise, which leads to the second contribution. The binaural ANC approach is proposed and applied for ITE HAs. The real-time experiments demonstrate the advantages of the binaural approach in terms of improvement of the causality situation and the low-frequency noise reduction performance, respectively. Moreover, the binaural ANC algorithm makes a better job for multiple noise sources scenarios. The primary stage of HAs ANC research shows that the binaural ANC algorithm can be applied not only for headphones, but also for other two-channel multimedia systems. The HAs ANC applications show similar behavior of the proposed binaural ANC algorithm, similar to the headphones case. The binaural ANC algorithm improves the “worst” channel multiple-noise reduction performance by 3-5 dB. However, the most useful ITE HAs configuration can cause the occlusion effect issue. Therefore, the adaptive occlusion effect canceller is applied to the binaural ANC algorithms for HAs to

attenuate the occlusion effect. The experimental results show that the adaptive occlusion effect canceller is able to attenuate the occlusion effect by about 15 dB.

Chapter 7

Conclusions and Future Work

This chapter summarizes the main findings and contributions of this thesis and explores future works. The aim of the future works is to extend the current investigations and to implement all parts of this thesis into one embedded chipset for the real noise reduction system for headphones/HAs.

7.1 Conclusions

The major research question of this thesis is the development and implementation of a high-efficiency noise reduction system for headphones based on the ANC algorithm. There are a lot of noise-cancellation headphones presented in the commercial market. However, most of them cannot fully satisfy user needs and preferences. Therefore, it was decided to equip conventional ANC algorithm for headphones with additional techniques to get an integrated noise reduction system for headphones, which is able to improve noise reduction results and perceptual quality of the sound in noisy environment.

Firstly, we focused on the human's hearing system. The human's hearing system has plenty of psychoacoustic features, which can be useful for noise reduction systems. It was noted that not all noise components are audible in the presence of the target sound. Therefore, the psychoacoustic model was involved in the conventional subband ANC algorithm in order to define the audibility of noise components and to reduce only audible noise. The objective psychoacoustic evaluations are more important than pure noise reduction results in terms of sound perception for headphones applications. The proposed psychoacoustic subband ANC algorithm showed similar objective psychoacoustic evaluations results as a conventional subband ANC algorithm. However, it requires less computational resources and computational time

because it processes only frequency bands with audible noise components. Thus, we proved that it is not necessary to process inaudible noise components because their reduction does not introduce any benefits for sound perception. Moreover, computational saving allows us to introduce additional techniques to be integrated into the psychoacoustic subband ANC algorithm in order to improve noise reduction performance and perceptual quality of the sound.

Secondly, this thesis focused on the aim to improve the perceptual quality of the target sound together with the improvement of the noise reduction results. Therefore, the psychoacoustic model was extended in order to implement the psychoacoustic masking algorithm. The psychoacoustic masking acts as the second stage of the noise reduction system after the psychoacoustic subband ANC algorithm. The goal of energy masking is to mask out the residual and high-frequency noise components. The proposed noise reduction system is highly integrated, there are strong connections between all parts and algorithms of the full system. The objective and subjective psychoacoustic evaluations proved that the proposed integrated psychoacoustic subband ANC and masking system achieved better perceptual quality compare to other related noise reduction approaches. Comparisons were made in terms of loudness, sharpness, and roughness for objective evaluations and terms of pleasantness sound scores and noise reduction scores for subjective evaluations. The major advantage of the proposed integrated system is the improvements in the perceptual experience, which is much more important for the users.

Thirdly, the different environmental noise scenarios were investigated. It is a fact that the performance of the conventional (bilateral) ANC algorithm for headphones significantly drops for multiple noise sources. Especially, if noise sources are completely different and placed in different directions. Unfortunately, in real-life, noise sources are everywhere. The binaural ANC algorithm was proposed based on the idea of sharing references and adaptive filters' inputs between the left and right channels of headphones. The real-time experiments for several independent single noise sources and a combination of multiple noise sources, placed at the different directions, showed that the proposed binaural ANC algorithm helps to improve the causality situation for some noise sources directions and also outperforms bilateral ANC algorithm in most of

multiple noise sources scenarios. However, the binaural ANC algorithm is not always better. The performances of binaural and bilateral ANC algorithms strictly depend on the number of noise sources, their types, and directions. The bilateral ANC algorithm has better noise reduction performance for the cases when noise sources are completely different in terms of frequency content and placed in different directions. This observation leads to the next part of this thesis.

Fourthly, the combined bilateral and binaural ANC (CBBANC) algorithm was proposed, developed and implemented. The CBBANC algorithm is able to select the “best” (bilateral or binaural) ANC solution according to the environmental noise scenario. The selection algorithm was proposed and implemented based on the coherence method, which defines “best” ANC implementation. Real-time experiments proved that the proposed CBBANC algorithm selects correct ANC implementation based on the environmental noise situation. The real-time experiments showed that the proposed CBBANC algorithm is an efficient solution for headphones ANC applications and it can be implemented without additional hardware resources.

Lastly, it was decided to check if the proposed binaural ANC algorithm will be efficient for other two-channel hearing devices. Therefore, the binaural ANC algorithm was extended to hearing aids' needs. The ITE hearing aids prototypes were used to conduct real-time binaural ANC experiments for hearing aids. The binaural ANC algorithm helps to solve the causality issue for most of the noise directions. It is useful for hearing aids applications because of their small size and limited distance between the reference and error microphones. On average, the proposed binaural ANC algorithm improves noise reduction performance of the “worst” channel by 4-6 dB. Therefore, it was proved that binaural and CBBANC algorithms are useful not only for headphones, but also for HAs systems based on the ANC approach.

7.2 Future Works

Through the investigations and the proposed approaches presented in this thesis, there are several extensions for future works. The future work can be divided into two categories: headphones future work and hearing aids future work. Firstly, the proposed integrated psychoacoustic subband ANC and masking algorithm can be improved by the further investigation and extension of the musical genres masking setup. Currently, this study is not fully completed. The proper implementation of the masking modes, based on the musical genre or the type of the environmental noise, assumes the fixed gain coefficients for the critical bands. Such an approach should be useful for real-time applications because it can decrease time delays of the masking procedure. There are three possible ways of switching between the masking modes. The simplest one is the manual approach, users select the masking based on their knowledge about the musical genre, which they listen to, or type of the dominant environmental noise. The second way is to connect the proposed method with music collection library of the user and apply music genres from it. The third way is to introduce artificial intelligence (AI) approach, which will be able to automatically switch between masking modes. It is obvious that AI approach will introduce additional time delays. However, the idea is to implement the simple classification system, which should take no longer time than the masking procedure.

Secondly, the proposed binaural and CBBANC algorithms were evaluated only for two noise sources and diffuse field noise. Therefore, it can be useful to evaluate the proposed algorithms for more than two noise sources, placed in different directions. These experiments can help to better understand the behavior of the proposed algorithms and prove the advantages of these algorithms.

The third extension for future work is more general. It is necessary to combine and implement integrated psychoacoustic subband CBBANC and masking system to extend its application from the experimental headphones prototype to the real commercial headphones. However, there are several challenges and issues. The noise-cancellation headphones performance should be independent of the types of devices. Therefore, all processing units should be

embedded in the headphones. The proposed noise reduction system consists of many parts, such as the ANC algorithm, psychoacoustic model, coherence measurements, which should work in parallel and should not degrade the performance of each other. The noise reduction system should operate in real-time without significant delays. Therefore, a possible solution is to find small-sized and powerful chipset, which is able to perform all processing tasks. In addition, computational requirements for the fully integrated system must be sufficiently reduced to meet real-time and high sampling rate. This solution requires additional investigations in order to define which parts and modules of the proposed system can be sacrificed or implemented in a more simple way.

The fourth area of the future works is about hearing aids. It is necessary to note that HAs ANC research is not fully completed. In order to completed HAs ANC research, it is still necessary to conduct more complicated experiments for different noise sources, placed in different directions. Moreover, the proposed HAs configuration is suitable for the experimental prototype. However, it is not applicable to real-life hearing aids because of the big size of the error microphone, which can be very uncomfortable inside the ear canal. Moreover, the proposed configuration of the ANC HAs should be evaluated through the speech intelligibility index system. Also, the binaural ANC algorithm for hearing aids operates in a similar way as headphones ANC application. It blocks all environmental sounds except speech, which is defined by simple VAD. Such an approach cannot satisfy the needs of modern hearing aids. Therefore, the next stage of this research is to develop and implement an algorithm, which will be able to define sound types, which must be blocked, and types, which must be passed through. It can be implemented on the base of, so-called, selective ANC algorithm [166].

Finally, there is an idea to extend binaural and CBBANC algorithms to multiple (more than two) channels systems. The proposed approach can be used to implement a new multi-channel ANC [167] algorithm. The multiple noise sources situation, noise types, and directions also cause issues for the multi-channel ANC systems. Especially, it becomes obvious for open-area real-time applications. Nowadays, multi-channel ANC algorithms are widely used for several applications [168] - [169]. Therefore, the working principles and ideas of

binaural and CBBANC algorithms can modify the conventional multi-channel ANC algorithm and improve noise reduction performance for its applications [170].

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Appendix A: Hardware Specifications

A.1 DSP Board TMS320C6713DSK Specification

The TMS320C67x DSPs are the floating-point DSP family in the TMS320C6000 DSP platform. The TMS320C6713 (C6713) device is based on the high-performance, advanced VelociTI very-long-instruction-word (VLIW) architecture developed by Texas Instruments (TI), making this DSP an excellent choice for multichannel and multifunction applications. With a performance of up to 1 giga floating-point operations per second (GFLOPS) at a clock rate of 167 MHz, the C6701 offers cost-effective solutions to high-performance DSP programming challenges. The C6713 DSP possesses the operational flexibility of high-speed controllers and the numerical capability of array processors. This processor has 32 general-purpose registers of 32-bit word length and eight highly independent functional units. The eight functional units provide four floating-/fixed-point ALUs, two fixed-point ALUs, and two floating-/fixed-point multipliers. The C6713 can produce two multiply-accumulates (MACs) per cycle for a total of 334 million MACs per second (MMACS). The C6713 DSP also has application-specific hardware logic, on-chip memory, and additional on-chip peripherals. The C6713 includes a large bank of on-chip memory and has a powerful and diverse set of peripherals. Program memory consists of a 64K-byte block that is user-configurable as a cache or memory-mapped program space. Data memory consists of two 32K-byte blocks of RAM. The peripheral set includes two multichannel buffered serial ports (McBSPs), two general-purpose timers, a host-port interface (HPI), and a glueless external memory interface (EMIF) capable of interfacing to SDRAM or SBSRAM and asynchronous peripherals.

Table A.1 C6713 Processor characteristics

Hardware Features		C6713
Peripherals	EMIF	1
	DMA	4-Channel
	HPI	1
	McBSPs	2
	32-Bit Timers	2
Internal Program Memory	Bytes	64K
	Organization	64K Bytes Cache/Mapped Program
Internal Data Memory	Bytes	64K
	Organization	2 Blocks: Eight 16-Bit Banks per Block 50/50 Split
Frequency	MHz	120, 150, 167
Cycle Time	ns	6 ns (6701-167); 6.7 ns (6701-150); 8.3 ns (6701-120)
Voltage	Core (V)	1.8 (6701-120, -150) 1.9 (6701-167 only)
	I/O (V)	3.3
PLL Options	CLKIN frequency multiplier	Bypass (x1), x4
BGA Package	35x35 mm	352-pin GJC
Process Technology	μm	0.18 μm
Product Status	Product Preview (PP) Advance Information (AI) Production Data (PD)	PD

A.2 KEMAR Dummy Head Specifications

The KEMAR head and torso simulator was introduced by Knowles in 1972 and quickly became the industry standard for hearing-aid manufacturers and research audiologists. The GRAS KEMAR has the same dimensions and acoustical properties as the original KEMAR from 1972 and is 100% backward compatible. When fitted with pinna simulator, ear canal extension, and IEC 60318-4 Ear Simulator, KEMAR closely mimics the acoustic properties of the human ear.

KEMAR meets the international standards as specified by IEC: 60318-7 and ANSI: S3.36, S3.25. The 45BB KEMAR is a non-configured KEMAR - without a mouth simulator. The 45BC KEMAR is identical, except that it has a built-in Mouth Simulator.

The major difference between KEMAR and the standard commercially available head and torso simulators (HATS) is that KEMAR is built on large statistical research of the average human body – meaning that the KEMAR has the same acoustical properties as an average human, including distinct facial features. Therefore it provides acoustic diffraction similar to that encountered around the median human head and torso, both in the proximity and in the far-field. Because of its anthropometric shape, it does so more realistically than any other manikin. KEMAR is the only manikin with a changeable ear-to-shoulder ratio simulating both male and female median values.

Table A.2 KEMAR dummy head specification

Temperature range, operation	°C/°F	-30 to 60/-22 to 140
Temperature range, storage	°C/°F	-40 to 65/-40 to 149
Humidity range non-condensing	%RH	0 to 95%
ANSI standard		S3.36, S3.25
IEC standard		60318-7
Weight	g/oz	11.45 k/404

A.3 Beyerdynamic – Custom One Plus Headphones Specifications

Custom One Pro Plus is a professional headphone for studio and home applications. A special feature of this headphone is the changeable sound which can be selected in four stages from an analytical sound to a rich, full bass via the “Custom Sound Slider” bass reflex vents at the housing shells. The versatile design with replaceable accessories gives the headphone a special individuality. With the 16 supplied different covers the look of the headphone can always be changed. By purchasing more covers, rings, ear and headband pads the user can change the look of the headphone at any time. The connecting cable is single-sided and detachable. The delivery includes one 1.30 m long cable with remote control and microphone for the use with smartphones and tablet computers. More cables are available in different versions and lengths for most various applications. The movable yokes and adjustable

headband of spring steel allow a perfect fit for each head size. Soft, replaceable ear and headband pads ensure a pleasant comfort of wearing.

Table A.3 Beyerdynamic - Custom One Pro Plus headphones specifications

Transducer type	Dynamic
Operating principle	Closed
Frequency response	5 Hz – 35000 Hz
Nominal impedance	16 Ω
Nominal SPL	96 dB
Max. SPL	116 dB
T.H.D.	< 0.2%
Power handling capacity	100 mW
Sound coupling to the ear	Circumaural
Ambient noise attenuation	Approx. 18 dBA
Headband pressure	Approx. 3.5 N
Weight without cable	290 g.
Length and type of cables	Single-sided cable, 1.3 m
Connector	Gold-plated mini stereo jack plug (3.5 mm)

Appendix B: Real-time Experimental Arrangements

B.1 The Microphones Positions and Experimental Arrangement for Single- and Multiple-noise Sources Scenarios

Most of real-time experiments are conducted in the anechoic chamber to prevent the environmental influence on the experimental results. Figures B1 and B2 shows the positions of the error and reference microphones for the real-time experiments.

Figure B.1 – Reference and error microphone's positions (Position #1) [116]

Figure B.2 – Real-time experiments' arrangement in the anechoic chamber [116]

Figure B.3 shows the position of the inner microphone position to measure performance of the commercial ANC headphones.

Figure B.3 – Position of the microphone to capture residual noise and evaluate commercial ANC headphones performance

B.2 The Diffused Field Experimental Setup

Figure B.4 shows the diffuse field experimental setup. This experiment is conducted in the university reverberant meeting room.

Figure B.4 – Experimental arrangement for diffuse field noise source

B.3 The Microphones Positions for The HAs Experiments

The HAs configurations #1 and #2 are shown in Figures B.5 and B.6, respectively.

Figure B.5 – ITE HAs configuration #1

Figure B.2 – ITE HAs configuration #2