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ADVANCED CONTROL DESIGN FOR HDD IN MOBILE CONSUMER DEVICES

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

2011

Statement of Originality

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

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Date

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WANG JIANYI

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Summary

As the HDD finds more applications in various mobile consumer devices, HDD servo control needs to improve the performance in the seeking acoustics and vibration rejection. This research provides feasible solutions to these two problems. The work described in this thesis is summarized as follows:

A new seeking controller for minimizing the acoustics is proposed. A systematic way of designing the seek controller with acoustics into consideration is given. The Two-Degree-Of-Freedom (TDOF) model reference controller is employed. The sinusoidal wave is used as the model reference input to produce the smooth current profile. The voltage saturation is taken into account in the control design so that the single seeking controller can be applied to full span of seek length. An acoustics factor is used as a controller input to easily tune the acoustics performance. Both simulation and experimental results are presented.

To handle various external vibrations, two kinds of vibration rejection schemes are proposed in this research:

1. An add-on loop gain booster algorithm is used to deal with the pink noise and the linear/rotational vibrations with relatively low amplitude. The

add-on feature will be turned on only in the specific vibration environment. The scheme comprises two parts: the vibration detection through analysis of the vibration sensor output or PES and the vibration compensation through the add-on feature. The transient response in switching on/off the add-on feature is successfully shortened by the reset control. Reset Integral-Derivative Element (RIDE) is adopted to form the reset controller. The scheme is implemented in real HDD and produces the satisfactory experimental results under various vibrations.

2. Two adaptive filtering based algorithms are developed to reject the pure tone disturbance and the linear/rotational vibrations with high amplitude: Least Mean Square (LMS) and Recursive Least Square (RLS).

The design of a Leaky Normalized Filtered-X LMS algorithm is demonstrated. The normalized LMS algorithm will make LMS algorithm be more robust with respect to power variations of the input vector and increase the convergence speed of the LMS algorithm. The leaky LMS can help mitigate the problem of accumulated quantization error in implementation. The Filtered-X LMS is derived. The algorithm is implemented in a real HDD. The experimental results show significant PES reduction in pure tone test and linear/rotational vibration tests.

The development of the Weighted QRD-based Filtered-X RLS in HDDs is presented. The weighted RLS is suitable for time-varying environment. The QR-Decomposition based RLS can solve the problem of numerical stability in implementation. Simulation is done in Simulink. A real-time model is used and the input data is collected in the real HDD under vibrations. The

simulation results prove the effectiveness of algorithm.

Nomenclature

The following abbreviations are frequently used throughout this thesis:

BPI	Bits Per Inch
DSA	Digital Signal Analyzer
FIR	Finite Impulse Response
HDD	Hard Disk Drive
IVC	Initial Value Compensation
LDV	Laser Doppler Vibrometer
LMS	Least Mean Square
NRRO	Non Repeatable Runout
PES	Position Error Signal
PTOS	Proximate Time Optimal Servomechanism
PZT	Lead-zirconate-titanate
RIDE	Reset Integral Derivative Element
RLS	Recursive Least Square

RPM	Revolutions Per Minute
RRO	Repeatable Runout
R/W	Read/Write
TDOF	Two Degree Of Freedom
TMR	Track Misregistration
TPI	Tracks Per Inch
TP	Track Pitch
VCM	Voice Coil Motor

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Chapter 1

Introduction

1.1 Background

1.1.1 HDD Applications in Mobile Devices

Global demand for data storage continues to grow at a fantastic pace: in 2009, the amount of digital information created and replicated in the world was 800,000 petabytes; the number in 2010 will grow to almost 1.2 million petabytes and in 2020 it will be 44 times as big as in 2009 [1] (A petabyte is a million gigabytes). At the same time, the growth of available storage cannot meet the demand. For the first time, in 2007, the amount of digital information created exceeded the available storage. That inflection point has since become a gulf that continues to expand [2].

Among all kinds of storage including the HDD, the optical drive, the tape, the

flash-based solid state drive, the HDD maintains the most important data storage medium because of its reliability, cost efficiency and fast-growing capacity. In 2007, the HDD accounted for 56% of digital data storage [2]. The HDD continues to provide more storage capacity every year, but with the same or smaller size and the increasing areal density (areal density refers to the amount of data that can be stored in a unit of area). In 1956, when IBM introduced the first disk drive, it could only store 2,000 bits per square inch, a measure commonly referred to as areal density. Today disks routinely store more than 100 billion bits per square inch. Areal density growth of disks had once been as robust as doubling annually. In the last few years and for the foreseeable future, areal density is expected to double every 2–3 years [3]. At the same time, the cost per mega-byte for HDDs has dropped from \$100 in 1956 to less than 1 cent now. Furthermore, the performance, reliability, and data transfer rate have improved dramatically.

Besides its traditional utilization in PC and laptop, the HDD is being more widely used in the mobile compact computers and portable consumer electronics equipments such as digital video recorder (DVR), video camera, MP3 players and etc, as presented in Fig. 1.1.

For HDDs applied in the mobile consumer devices, the customers will be concerned about:

1. Acoustics performance. The HDD needs to be operating quietly so that the sound emitted by the HDD will not disturb the playing audio or video programmes;
2. Vibration rejection. The HDD should be able to maintain the smooth data

Figure 1.1: HDDs in Mobile Devices

transfer when exposed to the external vibrations coming from the speaker, the people walking or jogging and many other sources.

Therefore the performance requirements for HDDs used in the mobile consumer devices have been revised accordingly: the weight of the acoustics and vibration rejection in the performance matrix has increased significantly; and it has become a priority to reduce the operating sound and reject the vibration.

1.1.2 HDD Servo Systems

Introduction to the HDD

Fig. 1.2 demonstrates the inside view of an HDD after the cover is removed.

The HDD uses round, flat disks, which are called platters, coated on both sides

Figure 1.2: Inside View of an HDD

with a special media material designed to store information in the form of magnetic patterns. The platters are mounted with a hole cut in the center and stacked onto a spindle. The platters rotate at a high speed, driven by a special spindle motor connected to the spindle. Special electromagnetic read/write heads are mounted onto sliders and used to either record information onto the disk or to read information from it. The sliders are mounted onto arms, all of which are mechanically connected into a single assembly and positioned over the surface of the disk by an actuator. A logic board controls the activity of the other components and communicates with the rest of the PC.

Each surface of each platter on the disk can hold tens of billions of individual

bits of data. These are organized into larger "chunks" for convenience, and for easier and faster access to information. Each platter has two heads, one on the top of the platter and the other on the bottom, so an HDD with 1 platter has two surfaces and two heads. Each platter has its information recorded in concentric circles called tracks. And each track is further divided into sectors, each holding 512 bytes of information.

The entire HDD must be manufactured to high precision because of the extreme miniaturization of the components, and the importance of the HDD's role in the PC. The main part of the disk is isolated from outside air to avoid contaminants from getting onto the platters and damaging the read/write heads.

A typical job for an HDD, such as loading a file into a spreadsheet program, can involve the following operations:

1. The first step in accessing the disk is to locate the needed information. The operating system, system BIOS and possibly any special driver software for the disk, will determine the cylinder, head and sector that the system wants the drive to read. (A cylinder is equivalent to a track for addressing purposes).
2. In most cases the disk drive is already spinning. If it isn't (because power management has instructed the disk to "spin down" to save energy) then the drive's controller board will activate the spindle motor to "spin up" the drive to operating speed. The controller board interprets the address it has received for the read, and performs any necessary additional translation steps by taking into account of the characteristics of the drive.

3. The HDD's logic program then looks at the final number of the requested cylinder. The cylinder number tells the disk which track to look at on the surface of the disk. The board instructs the actuator to move the read/write heads to the appropriate track.
4. When the heads are in the correct positions, the controller activates the specified head. The head begins reading the track looking for the sector that was asked for. It waits for the disk to rotate the correct sector number under itself, and then reads the contents of the sector.
5. The controller board coordinates the flow of information from the HDD into a temporary storage area (buffer). It then sends the information over the HDD interface, usually to the system memory, satisfying the system's request for data.

Servo Mechanism

A head-positioning servomechanism is a control system, which positions the read/write heads (mounted on the actuator) in a disk drive, as shown in Fig. 1.3.

The Voice Coil Motor (VCM) consists of the Upper and Lower Magnets coil on the Head Stack Assembly. The VCM converts current flowing through it into force which causes Assembly to rotate about the pivot bearing. When an electrical current is passed through the motor a force is produced. Reversing the electrical current causes a force in the opposite direction.

The position signal is the only measurable feedback signal of the HDD servo

Figure 1.3: HDD Servo Control Systems

system. Position information is embedded in the servo sectors along the data tracks at equally-spaced angles with user data sectors in between. User data sectors and servo information sectors are interleaved in a track as if the servo sectors are embedded in the data sectors. The number and the width of the servo sectors should be minimized to allow more space and time for user data recording. Servo sectors are pre-written on the disk before the disk can be used. Servo writing is performed by precision servo writers.

Demodulator is a hardware block that recovers the servo information from data read from the disk. The stored data in servo sectors then can be demodulated into the track number and the offset to the track center. In an embedded servo system, the position data can only be obtained in discrete-time format. Thus, its servo system is discrete in nature. The product of the spindle speed and the

number of sectors determine its sampling rate, i.e.

$$F_s = RPM/60 * N_s \quad (1.1)$$

where F_s is the sampling frequency, RPM is the spindle speed in the unit of revolutions per minute and N_s is the number of servo sector.

The function of servo controller is to move the read/write head from one track to the desired track quickly and smoothly and then keep it on the track center of the desired track as accurately as possible so that the tracks can be put together closer (higher track density). To achieve this, seeking and track following controllers are usually used.

Conventional seeking controllers focus on shortening the seeking time or reducing the seeking-induced vibration. To minimize the access time, the driving current to the actuator should reach the maximum during seeking and therefore the saturation must be taken into consideration. For time-optimal control, bang-bang control is known to provide the time optimal solution, where maximum acceleration and deceleration are used. Unfortunately, time-optimal control cannot be implemented directly into many practical applications including the HDD. Reference [4] combines the time-optimal control and input shaping methods to reduce the mode excitation. The most widely-used seeking algorithm in industry is a revised optimal control algorithm, named as proximate time optimal servomechanism (PTOS) [5]-[7]. Many approaches resort to refinement of the algorithm of PTOS [8]-[11]. An improved version of the PTOS algorithm is proposed in [9] to provide more freedom in shaping the desired response primarily in the linear

regime. In reference [10], settling time is reduced by introducing a predetermined damping coefficient into PTOS to achieve novel damping scheduling. In references [12] and [13], the algorithm of Two-Degree-Of-Freedom is used to reduce seeking-induced suspension vibration and thus quickening the settling. Reference [14] focuses on the design of a unifying TDOF controller structure for both seeking and tracking to shorten the seeking and settling time.

For the tracking control, the classical control techniques, such as PID (Proportional plus Integral plus Derivative) and lead-lag compensators, are still widely used in the industry. To get better tracking performance, many control approaches have been studied. LQG (Linear Quadratic Gaussian) design optimizes the linear quadratic criterion and LTR (Loop Transfer Recovery) technique generates the estimator, resulting in the output feedback loop the same as the full state feedback system [15]-[18]. Some efforts are put in robust control design; H_2/H_∞ controllers are derived based on the minimization of H_2 -norm/ H_∞ -norm of certain system transfer functions [19]-[23]. The applications of some adaptive control are also studied [24]-[26]. In recent years, some new nonlinear control algorithms [27]-[30] have been introduced and developed with the aim to improve the HDD servo performance by the means of breaking the performance limitations in linear control systems.

Due to various disturbance sources, noises and mechanical modes existing in HDDs, the tracking controller alone is insufficient for accurate positioning; therefore in the HDD servo control design, the tracking controller plays the role of main feedback controller, and some other compensation or cancelation methods are resorted to improve the tracking performance:

Repeatable runout compensation

The repeatable runout (RRO) of HDDs can be caused by a series of factors: the eccentricity of the track that is an offset of the track center with respect to the spindle center; bearing geometry and wear; motor geometry and track irregularity generated in servo writing process. The frequencies of RRO are integer multiples of the frequency of rotation of the disk drive. In general, there exist two approaches to reject RRO [31]: (1) feedback control based on the internal model principle, and (2) identification and feedforward control. Many versions of these techniques have been proposed to deal with RRO [32]-[36].

Disturbance observer

The classical disturbance observer is used in HDDs to compensate the force of flexible cable (ribbon cable), the external disturbance, the pivot friction force, etc [5],[37]-[41]. It estimates an equivalent disturbance by taking the difference between the actual control input and the predicted total input. The predicted control input is obtained by processing the plant output via an approximate inverse of the nominal plant dynamics. It includes an approximation, because the actual inverse is not realizable.

Mechanical mode cancelation

An HDD comprises multiple mechanical structures, such as the actuator, the suspension, the pivot bearing, and each mechanical component has its own resonance mode, which can be excited by external energy source. Mechanical resonances may severely degrade the drive performance in both seeking mode and track following mode, especially for high TPI HDD drives.

Notch filters have been well used to avoid amplifying the resonance mode [42], [43]. If the resonance can be identified, the notch filters can be adaptive [44]-[47]. To save phase drop and to deal with the modes above nyquist frequency, multi-rate notch filters have been widely adopted [48]-[50].

Calibration

To achieve better seeking and tracking performance, various calibrations are utilized in industry to compensate for the physical imperfection in the disc drives, such as the force constant calibration [51]-[53] and linearization for PES [54]-[58].

Dual stage servo control

The bandwidth of VCM servo control system is limited by the dynamics of VCM actuator. A lightweight, secondary-stage actuator placed near the head-slider is used in combination with VCM to increase the accuracy of position regulation [59]. In such a dual-stage servo system, VCM works for both seeking and tracking, and micro-actuator works mainly for tracking operation or very short seeking. Various control schemes are studied for dual stage servo control [60]-[66].

1.2 Motivations

As mentioned earlier, for HDDs used in various mobile consumer devices, the acoustics and the vibration rejection have been two critical performance indices. To meet the stringent customer requirements, servo control plays a vital role in

improving the performance in these two aspects.

Acoustics

Acoustics is the science of sound; and sound is mechanic vibration and/or mechanic waves in elastic media [67]. A sound source oscillates and brings the surrounding air into motion. The compressability and mass of the air cause these oscillations to be transmitted to the listener's ear. The sound incident at a point has two main distinguishing attributes: the sound pressure and the frequency. The hearing range of the human beings stays at 16-16,000 Hz. Humans use sound to communicate, and so it is not surprising that their hearing is the most sensitive over the frequency range covered by human speech, which is from around 400 Hz to 5,000 Hz [68],[69].

The sound emitted by an HDD is normally excited by structural loading, namely, the sound of an HDD mainly comes from two sources: the spindle motor during spinning and the VCM actuator during seeking [70],[71]. If some significant mechanical modes are excited, the vibration of the actuator arms at resonance frequencies is another cause of the sound; but such kind of problems are solved effectively by notch filtering.

When the drive is in idle mode, i.e., the drive has spun up but the read/write head is not on the disk, the sound comes only from the spinning and the dominant exciting sources include spindle motor electromagnetic forces inherent in the operation of a motor, e.g., torque ripples and unbalanced magnetic pull and windage-induced noise. The reduction of the sound from the spinning mainly

depends on the improvement of the mechanical design and manufacturing, that is, motor bearing, motor shaft design and disk balance [72].

During seeking, VCM current is the dominant excitation source. The sound level is determined by the spectrum of the seeking current as an excitation, and the mechanical structure as a plant being excited to emit sound. The method of seek acoustic transfer function (ATF) approach is used to derive the acoustic transfer function that has seeking current as input and seeking acoustics as response [70],[73], and the studies have shown that the key to improve the seeking acoustics is to reduce the rate of seeking current thus lowering seeking power at high frequencies to avoid mechanical modes from being excited to generate noise [71],[74]. The difference of sound pressure level between the idle state and seeking is normally 4-6dB for today's HDDs [70]. Minimization of the difference has become one of the primary seeking control objectives for HDDs used in mobile consumer devices. On the other hand, decreasing the acoustic level normally leads to a slower seek [75], which is undesirable for HDD performance; therefore a balance between the seeking acoustics and the seeking speed should be achieved.

The efforts in the research on reduction of the seeking acoustics are limited. The scheme of [76] puts some intermediate values between two control voltages to reduce the rate of current change; the proposed method can accommodate any intermediate values and at the same time obtain closed-form solution with proper development of the recursive state equation. Although seeking acoustics is improved, a systematic way to design for acoustics is not given and the improvement on the acoustics level is limited. In [74], the acoustic level is lowered down through the minimization of the seeking current rate; a cost function for

minimizing jerk is introduced and the target trajectory is generated based on the optimal control theory with fixed initial and terminal conditions. The method does not take into consideration of the current saturation and the limit on the maximum velocity, so it can only be applied to short seeks. In the proposed method of [77], the sliding mode controller with a frequency-shaped switching line is designed for a feedforward controller. The advantage of this method is that a high frequency ingredient in the feedforward input can be eliminated by setting the frequency-shaped switching line.

Some practical methods are used in industry to improve the acoustic performance. A method for reducing seeking acoustics via a variable-bandwidth low-pass filter to filter out the high frequency noise is provided in [78]. The variable-bandwidth low-pass filter is applied to adaptively shape a control signal supplied to a VCM to move the head. The bandwidth of the variable-bandwidth low-pass filter is dependent upon head position relative to a target track. The scheme described in [79] is a trial-and-error method in three steps:

1. An empirical current control value is selected;
2. The acoustic output of the disk drive in response to the current is examined;
3. Repeat steps 1-2 until a selected empirical current control value achieves the desired acoustic output.

The method in [80] seeks the help from the host to provide different combinations of seeking speed and seeking acoustics. The host selects between the quiet and the fast modes, depending on which mode is more suitable for a particular application.

[81] tries to minimize the performance degradation by using different seeking profiles for different seeking lengths: a relatively longer seek weighs toward a relatively slower seeking profile and a relatively shorter seek weighs toward a relatively faster seeking profile. All these method can make some improvement on the seeking acoustics, but a systematic way is needed for low acoustics design.

In this research, a systematic design of seeking control for the acoustics is proposed and an acoustic factor is directly related to the seeking profile generation.

Vibration

Increase of the HDD capacity is achieved by the increase of the areal density of the disks. Both bit density, also named as linear density of tracks, and track density of disks must be increased for higher areal density. The former is measured in bits per inch (BPI), and the latter in tracks per inch (TPI). Areal density, in bits per square inch, is the multiplication of BPI and TPI. Increasing TPI involves interdisciplinary technological advances in the magnetic media, actuators design, disk platter material and thickness, and servo control design. The increase in TPI also demands better vibration rejection capability of HDDs, as narrower track pitch makes the HDD more subjective to the operating vibrations that can throw the head off-track more easily and deteriorate positioning accuracy of the read/write(R/W) head on the desired track, as a result, such vibrations impair data flow smoothness during reading and writing, or even spoil data on the disk.

At the same time, the applications of HDDs in various mobile consumer devices cause HDDs to be more exposed to the external vibrations coming from

the speaker, the people jogging or walking and many other sources. To reduce cost and weight of mobile devices, manufacturers typically fabricate the HDD mounting frame utilizing thin structural members. Therefore, a computer frame is a compliant object that makes it susceptible to vibrations. Such a mounting configuration results in the vulnerability of the disk drive to vibrations excited by external sources.

To ensure HDDs to perform well in various mobile devices, nowadays HDD customers request HDD manufacturers to have more diversified vibration tests on HDDs to simulate practical conditions. Linear/rotational vibration tests simulate the conditions when HDDs are subjected to some vibrations in low frequency, such as people jogging or cycling; the pure tone test can get the HDD response in a single-frequency shock event; and the purpose of pink noise test is to measure the performance of HDDs under the vibrations with wider frequency range, so as to ensure HDDs to perform well when the consumer devices are playing some audio/video programmes with the speaker on. The major difference of these vibration tests from one another is the vibration's frequency spectrum.

The purpose of linear/rotational vibration tests is to monitor the HDD performance under low frequency and high amplitude vibrations. Fig. 1.4 shows the spectrum of the output of an accelerometer-based vibration sensor, which is mounted on an HDD, under linear random vibration. The HDD is installed on a linear shaker. The pink noise is a signal whose power spectral density is inversely proportional to the frequency. Fig. 1.5 shows the spectrum of the sensor output when the same HDD is installed in a laptop computer that is playing the pink noise sound. The spectrum difference between the sensor output and the actual

pink noise is caused by the transmission path from the speaker to the vibration sensor. It can be seen that the vibration sensor output in pink noise environment mainly contains the signal from 500Hz to 1000Hz in the spectrum while in the linear vibration environment contains the signal from 0 to 500Hz in the spectrum. To ascertain good performance in both two tests, servo control needs to reject the vibration well in both of the frequency ranges.

Figure 1.4: Linear Vibration Spectrum

Conventionally disturbance observer [82]-[85] and loop shaping [16][86] are often used for the vibration rejection. Normally the efficiency of these methods depends on an accurate plant modeling, which makes them very sensitive to the variation of the plant parameters. Furthermore, the improvement on the disturbance rejection is limited in a frequency range and the disturbance rejection in other frequencies worsens. This is due to the well-known 'water-bed' effect [87]-[91]. Fig. 1.6 illustrates the water-bed effect. In the frequency range below the point 'x', sensitivity function 2 has greater attenuation on the disturbance

Figure 1.5: Pink Noise Spectrum

than sensitivity function 1; above the point 'x', sensitivity function 1 performs better. It is obvious that sensitivity function 2 is more suitable for handling linear vibration while sensitivity function 1 runs better in pink noise test. Attenuation in some frequencies is accompanied by amplification in some other frequencies; there is no single sensitivity function that can perform well in both frequency ranges.

The water-bed effect can be theoretically explained with the Bode's integral theorem [87],[92]:

For all closed-loop stable, discrete-time feedback systems, the sensitivity function S has to satisfy the following integral constraint:

$$\frac{1}{\pi} \int_0^\pi \ln|S(e^{j\phi})| d\phi = \sum_{i=1}^m \ln|\beta_i| \quad (1.2)$$

Figure 1.6: Water-Bed Effect

where β_i are the open-loop unstable poles of the system, m is the total number of unstable poles, and $\phi = \omega T$ where T is the sample period and ω is the frequency in radians/sec. The theorem simply states that:

$$\begin{array}{lcl} \text{The area of} & \text{the area of} & \\ \text{disturbance } (|S| > 1) = & \text{disturbance } (|S| < 1) + & \text{a non-negative} \\ \text{amplification} & \text{rejection} & \text{constant} \end{array}$$

Hence, any area of sensitivity reduction must be compensated by a finite area of sensitivity increase.

To avoid water-bed effect, some researchers have taken some efforts in nonlinear control for disturbance rejection or loop shaping [93],[94]. Reference [95] combines KYP-based linear design and the adaptive nonlinear compensation. In [96],[97],

control designs for dual stage actuator are utilized to improve the disturbance rejection of HDDs.

For linear vibration or rotational vibration with large amplitude, any linear loop shaping method is unable to obtain enough attenuation and at the same time maintain the stability of the system, so the capability to suppress such vibrations through loop shaping and disturbance observer is limited. Vibration sensor-based feedforward algorithms are proper solutions to the problem, because the feedforward compensation is outside the main control loop and those algorithms are not limited by the water-bed effect. The effect of the vibration on the position error is actively minimized via the feeding of the accelerometer signal in some form into a feedforward control loop. Some research has been done in this direction. In [98], a simple gain block from the accelerometer output to the feed forward input is used to compensate the effect of the linear vibration and the gain is a polynomial respective to the different location of the disk. Reference [99] uses the loop shaping and H_∞ to find a high order filter to represent the transfer function from the accelerometer to the control input. In [100],[101], the gain from the accelerometer to the control input is adaptive through LMS algorithm. In [102], both the fixed-parameter transfer function and adaptive LMS method are adopted for acceleration feedforward control.

In this research, two kinds of vibration handling methods are proposed: 1. an add-on loop gain booster scheme to 'avoid' the water-bed effect; 2. adaptive filtering-based acceleration feedforward control algorithms.

1.3 Objectives

This research aims to achieve the following objectives:

1. It tackles the servo control problems for HDDs used in the mobile consumer devices, wherein the acoustics and the vibration rejection are two critical performance indices;
2. The new seeking algorithm should be able to reduce the seeking acoustics significantly; a systematic design for seeking acoustics should be given and an acoustics-related factor should be included in the design of the seeking control;
3. A satisfactory balance between the seeking acoustics reduction and the seeking speed degradation should be obtained; i.e., the improvement on the acoustic level is not achieved by very slow seeks;
4. The vibration rejection schemes should be capable of handling various vibrations and at the same time will not degrade the performance in normal environment without vibrations;
5. An HDD with these schemes should obtain much performance improvement in the linear/rotational vibration tests, pure tone test and pink noise test;
6. The scheme should be able to handle linear vibration/rotational vibration with large amplitude;
7. The proposed methods should be cost-effective and feasible in real HDDs.

1.4 Contributions

The contributions of this thesis are as follows:

- Development of a new seeking control design for low acoustics. Two-Degree-Of-Freedom control is utilized. The sinusoidal wave is used as the reference input. The current saturation and the maximum velocity are taken into account of in the trajectory generation so that the single seeking controller can be applied to all seeking lengths. The acoustics factor is defined and included in the seeking control design.
- Buildup of the direct relationship between the acoustic level and the seeking profiles. A systematic way of design for acoustics is given. An acoustics factor is included in the reference trajectory generation so that the acoustics level can be adjusted via seek design to reach a compromise between the access time and the acoustics level.
- Implementation and experimentation of the new seeking algorithm. The algorithm is implemented in a real 2.5-inch HDD. The measurement of both the acoustics and the access time are performed. The seeking acoustics is greatly reduced without significant increase of the seeking time.
- Development of an add-on loop gain booster scheme for vibration rejection. It is an add-on scheme and the add-on feature will be turned on only in specific vibration environment. The add-on feature increases the loop gain over a selected frequency band for enhanced disturbance rejection in that frequency band. The method has advantages over conventional disturbance

observer in that it is not model-based, so it is less sensitive to the variation of the plant parameters. It also avoids obtaining disturbance observation through differentiation of the position signal, which will greatly amplify the noise in the position signal. The vibration rejection in some frequencies can be improved without the compromise of the performance in other frequencies.

- Development of vibration detection methods. Two kinds of vibration detection are proposed: one uses the filtered vibration sensor output to detect the different vibrations and the other is a sensorless method to determine which kind of vibration is existing via analysis of PES.
- Application of the reset control to shorten the transient response. The transient response caused by switching on/off of the add-on feature is shortened with a reset controller. RIDE (Reset Integral-Derivative Element) is adopted to form the reset controller.
- Implementation and experimentation of the add-on loop gain booster scheme. The algorithm is implemented in a real 2.5-inch HDD. The linear vibration test and pink noise test are performed. The proposed method can suppress the disturbance in one frequency range without the compromise of the performance in other frequency ranges.
- Development of two adaptive filtering-based acceleration feedforward algorithms for vibration rejection. Two linear accelerometers are used to sense both the linear vibration and rotational vibration. Filtered-X algorithm is included in both algorithms to help maintain the system stability and to

reduce the order of the adaptive filters.

- Development of the Leaky Normalized Filtered-X LMS in HDDs. The normalized LMS algorithm will make LMS algorithm be more robust with respect to power variations of the input vector and increase the convergence speed of the LMS algorithm. The leaky LMS can help mitigate the problem of accumulated quantization error in implementation.
- Implementation and experimentation of the Leaky Normalized Filtered-X LMS in HDDs. The algorithm is implemented in a real 2.5-inch HDD. The pure tone test, the linear vibration test and the rotational vibration test are performed. The experimental results show significant PES reduction in vibration environment.
- Development of the Weighted QRD-based Filtered-X RLS in HDDs. The weighted RLS is suitable for time-varying environment. The QR-Decomposition based RLS can solve the problem of numerical stability in implementation.
- Simulation of of the Weighted QRD-based Filtered-X RLS in HDDs. A real-time model, which simulates a real HDD under vibration , is built in Simulink. Real PES and the accelerometer output, which are collected in a 2.5-inch HDD under pure tone vibration, are used in the model. Simulation results demonstrate the effectiveness of the algorithm.

1.5 Thesis Outline

The thesis is comprised of eight chapters in the following structure:

Chapter 1: Introduction — Some background knowledge of HDDs is given. The challenges when an HDD is applied in mobile consumer devices are presented. The HDD servo system is described. The motivations and contributions of this thesis are listed and finally the organization of the thesis is given.

Chapter 2: Mathematical Model of HDD Head-positioning Servo System — This Chapter presents model of the VCM with a current driver. Both analytic derivation and system identification results are presented in this chapter.

Chapter 3: Two-Degree-Of-Freedom Seeking Control for Low Acoustics Of HDDs — A brief introduction to PTOS algorithm is given. The TDOF seeking control, and the designs of the estimator and the state feedback controller are presented. How the seeking trajectory is generated based on an acoustic factor is demonstrated. Simulation and experimental results are illustrated.

Chapter 4: Add-On loop gain booster for Vibration Rejection — Two vibration detection methods are introduced and a comparison has been made. The add-on feature is presented and the combined control law is derived. The application of the reset control to improve the transient response is presented. Simulation and experimental results are demonstrated.

Chapter 5: Adaptive Filtering Based Acceleration Feedforward Control for Vibration Rejection — Accelerometer-based feedforward control and the accelerometer that is used in this research are introduced. Two kinds of the adaptive filtering algorithms are described: LMS (Least Mean Square) and RLS (Recursive Least Square). The last section presents the Filtered-X algorithm.

Chapter 6: Vibration Rejection by Leaky Normalized Filtered-X LMS — The

Filtered-X LMS algorithm is derived. The normalized LMS and the leaky LMS are described. The Leaky Normalized Filtered-X LMS in HDDs is summarized. Simulation method and simulation results are given. Implementation and experimentation are demonstrated in the last section.

Chapter 7: Vibration Rejection by Weighted QRD-based Filtered-X RLS in HDDs

— An introduction to the exponentially weighted Least Square estimation is given. QR-Decomposition-based RLS is presented. The weighted QRD-based Filtered-X RLS algorithm in HDDs is summarized. Simulation method and simulation results are presented.

Chapter 8: Conclusion and Recommendations

— Conclusion for this research and recommendations for future research are given.

Chapter 2

Mathematical Model of HDD Head-positioning Servo Systems

2.1 Introduction

The head-positioning servo system is an electromechanical system and composed of the Voice Coil Motor (VCM) actuator and the amplifier that drives the current into the coil. The VCM driver can be either voltage or current amplifier. The current amplifier is better than the voltage amplifier because of the higher output impedance, so today HDDs with current amplifiers are much more widely used. The VCM driver used in this research is a current amplifier.

This chapter is organized as follows: Section 2.2 gives the model through analytical derivation. The rigid body model of VCM with a current driver is obtained. Resonance modes are added to the rigid body model. The model is verified by the

identification method in Section 2.3. Section 2.4 describes the power amplifier saturation. The disturbance model of HDD is given in 2.5.

2.2 Model Obtained by Analytical Derivation

2.2.1 Rigid Body Model

1) VCM

The data on an HDD is obtained by the read/write head, which is moved with the actuator. The actuator is powered by the VCM. Fig. 2.1 presents how the magnetic force is produced and applied to the rotary actuator.

Figure 2.1: Voice Coil Motor and the Actuator

Torque for a rotary actuator is given by [103]:

$$T = 2B_g L N r I_m = K_t I_m \quad (2.1)$$

where

T is the torque;

B_g is gap flux density;

L is the length of coil wire cutting the gap flux density;

I_m is the coil current of VCM;

r is the average distance from the bearing to the center of force;

N is the number of coil turns;

$K_t = 2B_g L N R$ is the torque constant, (oz-in/A);

The equation of motion for the rotary actuator is given by

$$T = J\alpha \quad (2.2)$$

where J is the moment inertia of the moving parts (oz-in/sec²) and α is the angular acceleration. The linear acceleration will be

$$a = \frac{K_t R}{J} I_m \quad (2.3)$$

where R is the radius of VCM actuator.

The HDD servo system is a sampled system and normally the acceleration is

represented in terms of track per sample, (2.3) can be converted to

$$a = \frac{K_t R T_s^2 TPI}{J} I_m \quad (2.4)$$

where T_s is the sampling period and TPI is the track density in terms of tracks per inch.

As the transfer function from the acceleration to the displacement is a double integrator, the transfer function from the current I_m to the displacement y will be:

$$\frac{y}{I_m} = \frac{K_t R T_s^2}{J} \frac{TPI}{S^2} \quad (2.5)$$

2) VCM with a Current Driver

The circuit, shown in Fig. 2.2, is a current amplifier to drive a VCM. It consists of an error amplifier, a power amplifier and a current sense amplifier. L_m and R_m are the inductance and the resistance of VCM respectively. An external sense resistor R_S in series with the motor is used to detect the load current. The five amplifiers, A1 to A5, together with the sense resistor make up a current control loop. The result is a transconductance amplifier from the DAC output voltage to the current delivered to the motor. R_F is the feedback resistor from the current sense amplifier output and R_{IN} is the input resistor for the DAC output.

The electrical dynamics can be described in the form of the transfer functions:

$$\frac{5R}{R}V_1 - \left(-\frac{5R}{R}V_1\right) = I_m R_s + I_m R_m + L_m I_m S \quad (2.6)$$

$$V_2 = I_m R_s \frac{2R}{R} \quad (2.7)$$

$$\frac{V_{dac}}{R_{IN}} = \frac{V_2}{R_F} + \frac{V_1}{R_C + \frac{1}{C_C S}} \quad (2.8)$$

Substitute (2.6) and (2.7) into (2.8),

$$\begin{aligned} \frac{V_{dac}}{R_{IN}} &= \frac{2I_m R_s}{R_F} + \frac{R_s + R_m + L_m S}{10} \frac{C_C S}{R_C C_C S + 1} I_m \\ &= I_m \left[\frac{2R_s}{R_F} + \frac{(R_s + R_m)C_C S}{10} \frac{\frac{L_m}{R_s + R_m} S + 1}{R_C C_C S + 1} \right] \end{aligned} \quad (2.9)$$

Through proper selection of R_s , R_C and C_C , a pole-zero cancelation can be realized,

$$\frac{L_m}{R_s + R_m} S + 1 = R_C C_C S + 1 \quad (2.10)$$

Then (2.9) becomes:

$$\frac{I_m}{V_{dac}} = \frac{R_F}{2R_s R_{IN}} \frac{1}{\frac{C_C R_F (R_s + R_m)}{20R_s} S + 1} \quad (2.11)$$

Usually the bandwidth of this current loop is much higher than that of the tracking/seeking control, thus in practice, the dynamics of the current amplifier is

often ignored and a constant gain is used as follows:

$$\frac{I_m}{V_{dac}} = \frac{R_F}{2R_S R_{IN}} \quad (2.12)$$

Then the model of VCM with a current driver, G_r , can be described by the transfer function from V_{dac} to y :

$$G_r = \frac{y}{V_{dac}} = \frac{y}{I_m} \frac{I_m}{V_{dac}} = \frac{R_F K_t R T_s^2}{2R_S R_{IN} J} \frac{TPI}{s^2} \frac{1}{s^2} = \frac{K}{s^2} \quad (2.13)$$

where $K = \frac{R_F K_t R T_s^2}{2R_S R_{IN} J} \frac{TPI}{s^2}$. (2.13) is called a rigid body model of an HDD.

2.2.2 Resonance Modes

Even though the simplified transfer function of the VCM with the driver is a double integrator (2.13), the performance requirements are so high that structural mechanics effects cannot be neglected. The main contribution of the structure effects is through the mechanical resonance [104],[105]. These flexible modes will reduce the system stability if ignored. A resonance mode can be characterized as follows:

$$G_m(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \quad (2.14)$$

where $\omega_n = 2\pi f_n$ corresponds to a single resonance frequency f_n ; ζ is the associated damping coefficient.

Normally VCM actuator has several significant mechanical modes and they can be incorporated into the actuator model in serial connections with the rigid body

model, as presented in Fig. 2.3. and the corresponding transfer function will be

$$\begin{aligned}
 G_p(s) &= G_r * G_{m1} * G_{m2} \cdots G_{mn} \\
 &= \frac{K}{s^2} \frac{\omega_1^2}{s^2 + 2\zeta_1\omega_1s + \omega_1^2} \frac{\omega_2^2}{s^2 + 2\zeta_2\omega_2s + \omega_2^2} \cdots \frac{\omega_n^2}{s^2 + 2\zeta_n\omega_ns + \omega_n^2}
 \end{aligned} \tag{2.15}$$

2.3 Model Obtained by Identification

A linear system is uniquely determined by its frequency response. To identify a plant model in frequency domain, persistent excitation is required. In HDD industry, sweeping sine signal is widely used to measure the VCM frequency response. The Dynamic Signal Analyzer (DSA) can generate the sweeping sine as the excitation source. The Laser Doppler Vibrometer (LDV) allows non-contacting measurement of velocity and displacement and thus can be used to measure the movement of an HDD R/W head. Since there is no additional sensor/transducer attached to actuators, the dynamics of the measured mechanical system is not changed. The input-output frequency characteristic of the actuator can then be easily obtained by FFT analysis, which can also be done by DSA. Figure 2.4 shows the identification setup.

The source signal from the DSA, a sweeping sine, is injected to the voice coil of an HDD. The source signal is connected to channel 1 of DSA. Channel 2 is the output of the LDV. Then the transfer function from channel 1 to channel 2 is just the identified model from the voltage input to the position output.

The measurement procedure is as follows:

1. Switch on the power supply to the drive. When the spindle motor has stabilized at its operating speed, input a DC offset voltage to VCM and position the actuator on the disk;
2. Focus the laser beam of the LDV on the head in the direction tangent to spin direction. Ensure that the signal indicator on the front panel of the Fiber Interferometer is strong;
3. Connect DSA source to DSA channel 1 and LDV output to DSA channel 2. Set DSA to frequency response measurement;
4. Inject the sweeping sine signal from DSA channel 1 into the voice coil. Measure the frequency response from 100Hz to the sampling frequency of the HDD.

The experiment is conducted on a commercial Seagate 2.5-inch HDD with 7200 rpm, 310k TPI and sampling frequency 29.9 kHz. The measurement result is presented in Fig. 2.5. The frequency response of the plant is well consistent with the transfer function (2.15): the plant is a double integrator in low frequency and has some resonance modes in high frequency, and thus (2.15) can be used as the mathematical model of head-positioning servo system.

2.4 Power Amplifier Saturation

If the voltage output of the power amplifier remains less than certain value (the supply value minus some small transistor voltage drop), it will continue to behave as a current source [5]. However, when the current demand exceeds that which

is physically possible given the finite power supply voltage, the current source fails to behave as a current driver. Instead, during saturation it behaves as a voltage source of constant value as shown in Fig. 2.6. During track seeking, the saturation of the power amplifier is utilized to deliver the maximum available current to the voice coil to obtain a fast seek.

2.5 Disturbance Modeling in HDDs

As discussed before, the nominal model of plant can be analytically obtained through the mechanical and electronic platform or online identification through experiment setup. However, the servo system consists of not only the plant, but also the disturbance and noise environment in which it operates. A typical disturbance model is demonstrated in Fig. 2.7.

In the experimentation of this research, force constant variation and PES nonlinearity are handled by the factory calibrations; spindle related RRO is canceled by the repetitive feedforward control that is based on internal model principle; flutter disturbance and sensor noise are handled by the baseline controller design. All above mentioned disturbances will not be addressed by this thesis. This research will focus on handling of the external vibration.

2.6 Summary

In this chapter, the mathematical model of head-positioning servo systems is firstly derived by the analytical method, then the model identification is performed to verify the analytical result. Power amplifier saturation is also taken into consideration. A typical disturbance model of HDD is given.

The mathematical model obtained in this chapter will be used in the design of the state feedback controller, the current estimator and notch filters in the subsequent chapters.

Figure 2.2: VCM Driver

Figure 2.3: Rigid Body Model with Resonance Modes

Figure 2.4: Model Identification Setup

Figure 2.5: Model Identification Result

Figure 2.6: Power Amplifier Saturation

Figure 2.7: Disturbance Modeling in HDDs

Chapter 3

Two-Degree-Of-Freedom Seeking Control for Low Acoustics Of HDDs

3.1 Introduction

The application of HDDs in mobile consumer devices demands a very quiet seek, but most of the conventional seek controllers focus on shortening the seek time or reducing the seek-induced vibration. Proximate time optimal servomechanism (PTOS) is the most widely used seeking algorithm in industry, so a brief introduction to PTOS will be given first in this chapter. Then a new seeking control design for low acoustics is proposed. The Two-Degree-Of-Freedom (TDOF) model reference controller is employed. The sinusoidal wave is used in the proposed design as

the reference input. The current saturation and the maximum velocity are taken into account in the trajectory generation so that the single seeking controller can be applied to all seek lengths. The acoustics factor is defined and related to trajectory generation so that the balance between the acoustics level and the access time can be achieved through tuning the acoustics factor. Experimental results of the new algorithm will be compared with that of PTOS algorithm.

This chapter is organized as follows: Section 3.2 gives a brief introduction on PTOS algorithm. Section 3.3 introduces the TDOF seek control. The designs of the estimator and controller are presented. Section 3.4 describes the trajectory generation and parameter determination. Simulation and experimental results are shown in Section 3.5 and Section 3.6.

3.2 Introduction to PTOS

The objective of time optimal control is to minimize the time for the movement. PTOS uses time optimal control for larger errors and linear control law for smaller errors. PTOS combines linear state feedback control law and time optimal law into a single control algorithm with smooth transfer from non-linear control to linear control. The control chatter in time optimal control is contributed by the infinite gain of the signum function. This function is replaced in PTOS by the saturation function, which has a constant finite slope for smaller values of the input argument. The switching trajectory in time optimal law has infinite slope at the origin, while the switching function for PTOS is a finite slope approximation of the time optimal trajectory. The block diagram for PTOS control is presented

in Fig. 3.1.

Figure 3.1: PTOS Block Diagram

The control law for PTOS is given by the following equations

$$u = k_2(v_c - \hat{v}) \quad (3.1)$$

$$v_c = \begin{cases} \frac{k_1}{k_2} y_e & \text{if } |y_e| \leq y_l \\ \text{sgn}(y_e) \left(\sqrt{2u_{max}\alpha|y_e|k_{plant}} - \frac{u_{max}}{k_2} \right) & \text{if } |y_e| > y_l \end{cases} \quad (3.2)$$

where $y_e = y_r - y$, $\hat{v}$ and y are estimated velocity and measured position respectively, y_r is the reference position, u is the control input and u_{max} is the limit for control input, k_1 and k_2 are the feedback gains, and y_l is the linear region limit.

The constraint relating the feedback gains, k_1 and k_2 , is:

$$k_2 = \sqrt{\frac{2k_1}{\alpha k_{plant}}} \quad (3.3)$$

where k_{plant} is the plant gain.

The linear region limit y_l is defined as

$$y_l = \frac{u_{max}}{k_1} \quad (3.4)$$

In equation (3.2), the positive factor $\alpha < 1$ is referred to as the acceleration discount factor, which is determined by the plant uncertainty and the sampling rate.

Let us assume that the seek direction is known and $y_e > 0$. Substitute (3.2) into (3.1),

$$u = k_2 \sqrt{2\alpha u_{max} k_{plant} |y_e|} - u_{max} - k_2 \hat{v}$$

Then substitute (3.3) into above equation,

$$u = 2\sqrt{k_1 u_{max} |y_e|} - u_{max} - k_2 \hat{v}$$

Before the seek enters the linear region, $y_e > y_l$, therefore

$$u = 2\sqrt{k_1 u_{max} |y_e|} - u_{max} - k_2 \hat{v} \geq u_{max} - k_2 \hat{v}$$

When the seek begins, $\hat{v} = 0$, therefore $u = u_{max}$, the control output will be increased from 0 to u_{max} immediately, thus the big jerk will produce the big sound and the seek acoustics will be very bad.

3.3 Design of a TDOF Seek Controller

3.3.1 The TDOF Control Loop

Model Reference seeks are moves performed using a feedforward current applied to the actuator. Some TDOF model reference feedforward methods have been used in HDD industry. [12] and [13] use TDOF to reduce seek induced suspension vibration and therefore make the settling easier. Seek time is reduced by TDOF control in [106]. In this research, TDOF Model reference feedforward control is used to reduce the seek acoustics.

The system shown in Fig. 3.2 is a typical Two-Degree-Of-Freedom system[107], where the system is subjected to the disturbance input $D(s)$ and the noise input $N(s)$, in addition to the reference input $R(s)$. C_1 and C_2 are transfer functions of two controllers. P is the transfer function of the plant. $U(s)$ is the controller output.

Figure 3.2: Two-Degree-Of-Freedom system

The closed-loop transfer function is given by,

$$G_C = \frac{Y(s)}{R(s)} = \frac{P(C_1 + C_2)}{1 + PC_1} \quad (3.5)$$

the sensitivity function

$$G_S = \frac{Y(s)}{D(s)} = \frac{1}{1 + PC_1} \quad (3.6)$$

and complimentary sensitivity function,

$$G_T = \frac{Y(s)}{N(s)} = \frac{PC_1}{1 + PC_1} \quad (3.7)$$

Hence we have

$$G_C = (PC_2 - 1)G_S + 1 \quad (3.8)$$

$$G_T = G_S - 1 \quad (3.9)$$

Clearly, if G_S is given, then G_T is fixed, but G_C is not fixed, because C_2 is independant of G_S , and thus, two transfer functions among these three functions G_S , G_T and G_C are independant. Hence, the system is a Two-Degree-Of-Freedom control system.

The overall control loop for seeking is presented in Fig. 3.3, which is a same-type TDOF control system as that in Fig. 3.2. The controller comprises a feedforward compensator and a feedback compensator. One of the advantages of TDOF control is that the designers can set the reference input as they need. As shown in Fig. 3.3, a desired feedforward current with saturation into consideration is fed into the trajectory generator to produce the trajectories of the feedforward current, the position and the velocity. The velocity trajectory is limited by the

allowable maximum velocity. Real position and the estimated velocity are compared with the trajectories to form position and velocity error terms. The errors then go through the controller to generate the control input. The addition of this control input and the feedforward current trajectory will be applied to the actuator to move it to the target position.

Figure 3.3: Two-Degree-Freedom model reference control

3.3.2 Estimator and Controller Design

As described in the Chapter 2, the HDD plant model can be approximated by a double integrator if the mechanical modes in high frequency can be handled by notch filters [5]. The only state that can be directly measured in HDDs is the read/write head position. As the velocity state is needed, a state observer is used to estimate the velocity.

Let the discrete-time plant model be defined as,

$$X(k+1) = \Phi X(k) + \Gamma u(k) \quad (3.10)$$

$$y(k) = HX(k) \quad (3.11)$$

where $X \equiv [y \ v]^T$ are states representing the position and the velocity, $\Phi \in \mathbb{R}^{2 \times 2}$, $\Gamma \in \mathbb{R}^{2 \times 1}$, and $H \in \mathbb{R}^{1 \times 2}$ are constant matrices respectively.

Let $\hat{X} \equiv [\hat{y} \ \hat{v}]^T$ represent the estimated position and velocity. In order to minimize control delay, a current estimator is selected [5]. The block diagram of the estimator is demonstrated in Fig. 3.4.

Figure 3.4: The block diagram of current estimator

The discrete-time current estimator is derived as follows:

$$\begin{aligned}
 \hat{X}(k+1) &= \Phi \hat{X}(k) + \Gamma u(k) + L[y(k+1) - H(\Phi \hat{X}(k) + \Gamma u(k))] \\
 &= (\Phi - LH\Phi) \hat{X}(k) + (\Gamma - LH\Gamma)u(k) + Ly(k+1) \\
 &= (\Phi - LH\Phi) \hat{X}(k) + (\Gamma - LH\Gamma)u(k) + LH(\Phi X(k) + \Gamma u(k)) \\
 &= (\Phi - LH\Phi) \hat{X}(k) + \Gamma u(k) + LH\Phi X(k)
 \end{aligned} \quad (3.12)$$

where L is the feedback gain matrix of the estimator.

The control law is

$$u(k) = -K\hat{X}(k) \quad (3.13)$$

where K is a gain matrix.

Substitute (3.13) into (3.12)

$$\hat{X}(k+1) = LH\Phi X(k) + (\Phi - \Gamma K - LH\Phi)\hat{X}(k)$$

The full system will be

$$\begin{bmatrix} X(k+1) \\ \hat{X}(k+1) \end{bmatrix} = \begin{bmatrix} \Phi & -\Gamma K \\ LH\Phi & \Phi - \Gamma K - LH\Phi \end{bmatrix} \begin{bmatrix} X(k) \\ \hat{X}(k) \end{bmatrix} \quad (3.14)$$

Taking the reference trajectories into consideration, the control law will be

$$u(k) = -K(\hat{X}(k) - R) + c \quad (3.15)$$

where c is the current trajectory, $R \equiv [s_R \ v_R]^T$, s_R and v_R are position and velocity trajectories respectively.

Substitute (3.15) into (3.10)

$$X(k+1) = \Phi X(k) - \Gamma K \hat{X}(k) + \Gamma K R + \Gamma c \quad (3.16)$$

Substitute (3.15) into (3.12),

$$\begin{aligned} \hat{X}(k+1) &= (\Phi - \Gamma K - LH\Phi + LH\Gamma K)\hat{X}(k) + (\Gamma - LH\Gamma)c + (\Gamma K - LH\Gamma K)R \\ &\quad + Ly(k+1) \\ &= LH\Phi X(k) + (\Phi - LH\Phi - \Gamma K)\hat{X}(k) + \Gamma K R + \Gamma c \end{aligned} \quad (3.17)$$

the full system will be

$$\begin{bmatrix} X(k+1) \\ \hat{X}(k+1) \end{bmatrix} = \begin{bmatrix} \Phi & -\Gamma K \\ LH\Phi & \Phi - \Gamma K - LH\Phi \end{bmatrix} \begin{bmatrix} X(k) \\ \hat{X}(k) \end{bmatrix} + \begin{bmatrix} \Gamma K & \Gamma \\ \Gamma K & \Gamma \end{bmatrix} \begin{bmatrix} R \\ c \end{bmatrix} \quad (3.18)$$

3.4 Trajectory Generation and Parameter Determination

3.4.1 Trajectory Generation

The sinusoidal wave is selected as the desired reference input for the following reasons:

1. The rate of sinusoidal wave is bounded and continuous; and it will be shown later that the rate of sinusoidal wave will be directly related to the acoustics performance;
2. The shape of the sinusoidal wave is suitable for a current profile: a complete period has both the acceleration and deceleration stages; the profile in the acceleration stage is symmetric to that in the deceleration stage;
3. the sinusoidal wave is easy to implement through look-up in a sine table that most of HDDs already have in the servo code.

To make the seek faster, the amplitude of the driving current should be as large as possible; in practical condition, though, the driving current is limited by the

maximum current that the electrical system can provide, as described in Chapter 2, therefore the current will have the saturation during seeking. On the other hand, the maximum seeking velocity is limited by the head flying capability, i. e., once the seeking velocity is greater than a threshold, the head will miss reading, read wrongly, or even scratch the media and spoil data recorded on the disk, which has to be avoided in HDDs. Therefore, both the current saturation and maximum velocity should be considered in the trajectory design. The current profile is shown in Fig. 3.5.

Figure 3.5: Current profile

Some denotations in Fig. 3.5 are:

A : The current saturation level

B : The amplitude of sinusoidal wave

T_1 : The time to reach the saturation

T_v : The duration when the velocity keeps its maximum value

T_f : The duration of half sinusoidal wave

According to Fig. 3.5, the current trajectory is obtained in (3.19). It is noteworthy that t counts from zero in the beginning of both acceleration and deceleration stages in all following calculations.

$$c = \begin{cases} B \sin(\pi \frac{t}{T_f}) & 0 < t_x < T_1 \\ A & T_1 < t_x < T_f - T_1 \\ B \sin(\pi \frac{t}{T_f}) & T_f - T_1 < t_x < T_f \\ 0 & T_f < t_x < T_f + T_v \\ -B \sin(\pi \frac{t}{T_f}) & T_f + T_v < t_x < T_f + T_v + T_1 \\ -A & T_f + T_v + T_1 < t_x < 2T_f + T_v - T_1 \\ -B \sin(\pi \frac{t}{T_f}) & 2T_f + T_v - T_1 < t_x < 2T_f + T_v \end{cases} \quad (3.19)$$

where c represents the actual current that will be injected.

It can be seen that both acceleration and deceleration stages are divided into three sub-stages: before saturation, saturation and after saturation. Between the acceleration stage and the deceleration stage, there is one more stage called coasting when the acceleration equals to zero and the velocity reaches its maximum.

The HDD plant model from the current to the position can be represented by a double integrator, so the transfer function from the current to the acceleration will only be a DC gain.

$$a = K_{plant}c \quad (3.20)$$

where a represents the acceleration.

Based on the current profile in (3.19), the profiles of the position and the velocity can be generated with the following two motion equations:

$$v = v_0 + \int_0^t a dt \quad (3.21)$$

$$s = s_0 + \int_0^t v dt \quad (3.22)$$

where v and s represent the velocity and the position. Therefore the velocity trajectory from 0 to T_f can be obtained as follows:

$$v_R = \begin{cases} C(1 - \cos(\pi \frac{t}{T_f})) & 0 < t_x < T_1 \\ C(1 - \cos(\pi \frac{T_1}{T_f})) + A(t - T_1) & T_1 < t_x < T_f - T_1 \\ C - 2C \cos(\pi \frac{T_1}{T_f}) + A(T_f - 2T_1) - C \cos(\pi \frac{t}{T_f}) & T_f - T_1 < t_x < T_f \end{cases} \quad (3.23)$$

where $C = \frac{BT_f}{\pi}$.

In the coasting period of T_f to $T_f + T_v$, the velocity will reach and keep its maximum,

$$\begin{aligned}
 V_{max} &= \int_0^{T_1} B \sin(\pi \frac{t}{T_f}) dt + A(T_f - 2T_1) + \int_{T_f - T_1}^{T_f} B \sin(\pi \frac{t}{T_f}) dt \\
 &= 2C - 2C \cos(\pi \frac{T_1}{T_f}) + A(T_f - 2T_1) \\
 T_f &< t_x < T_f + T_v
 \end{aligned} \tag{3.24}$$

Taking the advantage of the symmetric property of the sinusoidal wave, we can obtain the velocity for the deceleration stage easily.

$$v_R = \begin{cases} V_{max} - C(1 - \cos(\pi \frac{t}{T_f})) & T_f + T_v < t_x < T_f + T_v + T_1 \\ V_{max} - (C(1 - \cos(\pi \frac{T_1}{T_f})) + A(t - T_1)) & T_f + T_v + T_1 < t_x < 2T_f + T_v - T_1 \\ V_{max} - (C - 2C \cos(\pi \frac{T_1}{T_f}) + A(T_f - 2T_1) - C \cos(\pi \frac{t}{T_f})) & 2T_f + T_v - T_1 < t_x < 2T_f + T_v \end{cases} \tag{3.25}$$

The corresponding position trajectory can be obtained based on the velocity trajectories (3.23) (3.24) (3.25) and the motion equation (3.22). The position

trajectory in the acceleration stage is:

$$s_R = \begin{cases} Ct - \frac{C}{B} \sin(\pi \frac{t}{T_f}) & 0 < t_x < T_1 \\ M(t - T_1) + 0.5A(t - T_1)^2 & T_1 < t_x < T_f - T_1 \\ N + Mt - C \cos(\pi \frac{T_1}{T_f}) & \\ +A(T_f - 2T_1A)t + \frac{C}{B} \sin(\pi \frac{t}{T_f}) & T_f - T_1 < t_x < T_f \end{cases} \quad (3.26)$$

where

$$M = \frac{BT_f}{\pi} (1 - \cos(\pi \frac{T_1}{T_f}))$$

$$N = M(T_1 - T_f) - \frac{BT_f}{\pi} (T_1 - T_f) \cos(\pi \frac{T_1}{T_f}) + A(T_f - 2T_1A)(T_1 - T_f) - \frac{BT_f^2}{\pi^2} \sin(\pi \frac{T_1}{T_f})$$

The position trajectory in coasting period is proportional to the maximum velocity,

$$s_R = V_{max}(t - T_f) \quad T_f < t_x < T_f + T_v \quad (3.27)$$

The position trajectory in the deceleration stage can be deduced as follows:

$$s_R = \begin{cases} V_{max}t - Ct + \frac{C}{B} \sin(\pi \frac{t}{T_f}) & 0 < t_x < T_1 \\ V_{max}(t - T_1) - (M(t - T_1) + 0.5A(t - T_1)^2) & T_1 < t_x < T_f - T_1 \\ V_{max}(t - T(f) + T_1) - (N + Mt - C \cos(\pi \frac{T_1}{T_f})) & \\ +A(T_f - 2T_1A)t + \frac{C}{B} \sin(\pi \frac{t}{T_f}) & T_f - T_1 < t_x < T_f \end{cases} \quad (3.28)$$

Let S_1 , S_2 and S_3 represent the distances the head has moved in three sub-stages of acceleration respectively; S_4 represents the distance in coasting stage; and S_5 , S_6 and S_7 represent the distances in three sub-stages of deceleration. Based on the position trajectory (3.26) (3.27) and (3.28), we have

$$S_1 = \frac{1}{\pi}BT_1T_f - \frac{1}{\pi^2}BT_f^2 \sin(\pi \frac{T_1}{T_f}) \quad (3.29)$$

$$S_2 = M(T_f - 2T_1) + 0.5A(T_f - 2T_1)^2 \quad (3.30)$$

$$S_3 = N + MT_f - \frac{1}{\pi}BT_f^2 \cos(\pi \frac{T_1}{T_f}) + A(T_f - 2T_1)T_f - \frac{1}{\pi^2}BT_f^2 \sin(\pi \frac{T_f}{T_f}) \quad (3.31)$$

$$S_4 = V_{max}T_v \quad (3.32)$$

$$S_5 = V_{max}T_1 - \frac{1}{\pi}BT_1T_f + \frac{1}{\pi^2}BT_f^2 \sin(\pi \frac{T_1}{T_f}) \quad (3.33)$$

$$S_6 = V_{max}(T_f - 2T_1) - M(T_f - 2T_1) - 0.5A(T_f + 2T_1)^2 \quad (3.34)$$

$$S_7 = V_{max}T_1 - N - MT_f + \frac{1}{\pi}BT_f^2 \cos(\pi \frac{T_1}{T_f}) - A(T_f - 2T_1)T_f + \frac{1}{\pi^2}BT_f^2 \sin(\pi \frac{T_f}{T_f}) \quad (3.35)$$

The seek length S equals to the sum of the distances the head has moved in all sub-stages,

$$\begin{aligned} S &= S_1 + S_2 + S_3 + S_4 + S_5 + S_6 + S_7 \\ &= V_{max}(T_f + T_v) \end{aligned} \quad (3.36)$$

For very short seeks, the trajectories become much simpler: the current will not reach the saturation level and the velocity will not reach the velocity limit, so the current profile is specified as a pure sinusoidal wave and there will be no coasting

state, as shown in Fig. 3.6.

Figure 3.6: Current profile for short seeks

The current trajectory for short seek will be

$$a_s = B \sin\left(\pi \frac{t}{T_f}\right) \quad (3.37)$$

The velocity trajectory will be

$$v_s = \frac{1}{\pi} B T_f \left(1 - \cos\left(\pi \frac{t}{T_f}\right)\right) \quad (3.38)$$

The position trajectory will be

$$s_s = \frac{1}{\pi} B T_f \left(t - \frac{1}{\pi} T_f \sin\left(\pi \frac{t}{T_f}\right)\right) \quad (3.39)$$

The seek length S_s can be obtained easily as below

$$S_s = \frac{2}{\pi} B T_f^2 \quad (3.40)$$

3.4.2 Acoustics Factor and Parameters Determination

Before a seek starts, the seek destination will be provided by the HDD host; therefore the seek length is a known parameter; the maximum velocity is also pre-determined, and the maximum current is fixed as well. All the other parameters in trajectories (3.19) and (3.23)-(3.28) need to be determined.

1) Acoustics Factor

To achieve lower acoustics level, the jerk value (the rate of the seek current) will have to be minimized. For the current profile (3.19), the maximum jerk value is:

$$\max(jerk) = \max\left(\frac{da}{dt}\right) = \max\left(\frac{\pi B}{T_f} \cos\left(\pi \frac{t}{T_f}\right)\right) = \frac{\pi B}{T_f} \quad (3.41)$$

Define the acoustics factor α as:

$$\alpha = \frac{\pi B}{T_f} \quad (3.42)$$

The acoustics level of the seek will be decided by α . Lower α produces lower jerk value and thus quieter seek.

2) Parameter Determination

Since A is known, B , T_1 , T_v and T_f can be determined accordingly. Firstly, $\frac{T_1}{T_f}$ is set to be a constant: $D = \frac{T_1}{T_f}$, therefore

$$B = \frac{A}{\sin(\pi D)} \quad (3.43)$$

Rewrite (3.24) as:

$$V_{max} = \left(\frac{2B}{\pi} - \frac{2B}{\pi} \cos(\pi D) + A(1 - 2D) \right) T_f$$

Thus,

$$T_f = \frac{V_{max}}{\frac{2B}{\pi} - \frac{2B}{\pi} \cos(\pi D) + A(1 - 2D)} \quad (3.44)$$

T_1 will be

$$T_1 = DT_f \quad (3.45)$$

With the desired seek length S and maximum velocity V_{max} , according to (3.36), the coasting duration T_v can be obtained as below:

$$T_v = \frac{S}{V_{max}} - T_f \quad (3.46)$$

The relationship between the acoustics factor α and the other parameters can be obtained as follows,

$$\alpha = \frac{2B - 2B^2 \cos(\pi D) + \pi BA(1 - 2D)}{V_{max}} \quad (3.47)$$

Note that equation (3.47) relates the acoustics level to the seek profile directly. Therefore the acoustics level can be tuned via modification of the values of D or V_{max} . V_{max} can be set to different values for various seek lengths with the maximum limit imposed by the head flying capability.

For very short seeks, the current profile is fully specified as a sinusoidal wave (3.37), and the deduction of the relationship between the acoustics factor α becomes quite simple. According to 3.40,

$$T_f = \sqrt{\frac{\pi S_s}{2B}} \quad (3.48)$$

substitute 3.48 into 3.42,

$$\alpha = \frac{\sqrt{2\pi} B^{\frac{2}{3}}}{\sqrt{S_s}} \quad (3.49)$$

Given a seek length S_s , both the acoustics factor α and the seek time T_f are decided by the value of the amplitude of sinusoidal wave, B ; that is, bigger B will produce more noisy but faster seek; smaller B will produce quieter but slower seek.

3.5 Simulation Results

Simulation is done in Matlab. With the given current saturation value, the velocity limit and a predetermined acoustics factor, all parameters can be decided: the current trajectory is produced according to (3.19); the velocity trajectory is produced according to (3.23)-(3.25); and the position trajectory is produced according to (3.26)-(3.28). The trajectories of the current, the velocity, the po-

sition and the corresponding jerk are presented in Fig. 3.7. Bigger jerk value is observed in the acceleration and deceleration stages of the current; the velocity reaches its maximum at the coasting stage; and at the end of the seek, the current, the velocity and the distance become zero at the same time.

To demonstrate the effect of the acoustics factor, another set of trajectories is generated when a lower acoustics factor is used while the seek length, the saturation level and the maximum velocity limit are still set to be the same. Fig. 3.8 shows the profiles when lower acoustics factor is used. Lower acoustics factor produces smaller rate of the current, hence, in acceleration stage, it takes longer for the current to reach the saturation level and decrease to zero, and thus the velocity needs more time to reach the maximum; in deceleration stage, the velocity needs more time to decrease to the zero. Although the overall seek time is longer, the jerk value is much smaller and as a result, the acoustics performance will be greatly improved.

The effect of the velocity limit on the trajectories is shown in Fig. 3.9. Compared to Fig. 3.8, the maximum velocity is lower while all the other parameters are the same. It can be seen that it takes less time to reach the maximum velocity; the drive stays longer in coasting stage; the jerk is greater and the overall seek time is longer.

For short seeks, the current trajectory, the velocity trajectory and the position trajectory are produced according to (3.37), (3.38) and (3.39) respectively, as shown in the Fig. 3.10. The current is a pure sinusoidal wave, the jerk is continuous and there is no coasting stage during seek.

Figure 3.7: The trajectories with greater acoustics factor

3.6 Experimental Results

3.6.1 Experimental Setup

The experiment was conducted using a commercial 2.5-inch, 2-head Seagate drive with 7200 rpm, 310k TPI and sampling frequency 29.9 kHz. The code with the new seeking algorithm was downloaded to the drive. To completely evaluate the new algorithm, three kinds of measurement were performed:

- Seek Current. The seek current and the jerk for a half-stroke seek were measured. The current spectrum was analyzed;

Figure 3.8: The trajectories with smaller acoustics factor

- Sound pressure level. The drive is put in an acoustics chamber for sound pressure level measurement;
- Seek access time. The seek time for all seek lengths was measured.

For the purpose of the comparison, all measurements were conducted for both PTOS seek and the TDOF sinusoidal seek.

3.6.2 Seek Current

The comparison of the seek current and the jerk is shown in Fig. 3.11. The jerk of PTOS seek current is very high at the beginning of the acceleration stage,

Figure 3.9: The trajectories with lower velocity limit

the end of the acceleration stage, the beginning of the deceleration stage, and relatively low at the end of the deceleration stage because PTOS has a linear stage at the end of the seek. For the new sine TDOF seek, it is obvious that all peaks of the jerk have been reduced significantly.

The spectrum of the seek current is shown in the Fig. 3.12. In the frequency range 500-5000 Hz, where the human hearing is the most sensitive, the new sine TDOF controller significantly reduces the power of seeking current.

Figure 3.10: The trajectories for short seek

3.6.3 Sound Pressure Level

Sound pressure is the local pressure deviation from the ambient (average, or equilibrium) pressure caused by a sound wave. Sound pressure can be measured using a microphone in air. Sound pressure level (SPL) is a logarithmic measure of the effective sound pressure of a sound relative to a reference value. It is measured in decibels (dB) above a standard reference level.

The human ear is a sound pressure sensitive detector. It does not have a flat spectral sensitivity, so the sound pressure is often frequency weighted so that the measured level will match the perceived level. When weighted in this way the measurement is referred to as a sound level.

Figure 3.11: Current and Jerk Comparison

In this experiment, the sound pressure level measurement is conducted in a chamber, as shown in Fig. 3.13. The HDD is put on a table with flat and solid surface, and a microphone above is used to measure the sound pressure level.

The sound pressure level measurement is performed in three kinds of conditions:

1. Idle: the drive is spinning only and the head is parking in the ramp;
2. Half stroke seek: the drive is doing two-points seek and the seek length is half of the full stroke;
3. Random seek: the drive is doing seeks with random seek lengths.

Figure 3.12: Current Spectrum Comparison

Table 3.1: Sound Pressure Level Measurement (dBA)

Seek Algorithm\Drive Status	Idle (Drive spinning only)	Half Stroke Seek	Random Seek
PTOS	23.1	28.8	29.1
Sine TDOF	23.3	24.9	25.1

The difference of the acoustics measurement between the idle and half stroke seek or random seek is just the add-on acoustics caused by the seek. The measurement results for both PTOS and sine TDOF are demonstrated in Table 3.1. For half stroke seeks, the acoustics caused by seek has been lowered from 5.7dBA (for PTOS) to 1.6dBA (for Sine TDOF) and 72% reduction has been achieved. For random seeks, the acoustics caused by seek has been lowered from 6.0dBA (for PTOS) to 1.8dBA (for Sine TDOF) and 70% reduction has been achieved.

3.6.4 Seek Access Time

The seek time for different seek length is a critical performance index because the read/write throughput performance is directly related to it. If the improvement in the acoustics compromises the access time too much, the algorithm will not be accepted. PTOS can achieve very good result in seek time measurement. Fig. 3.14 shows the seek time comparison between two seeking algorithms. The seek time of the proposed TDOF seek is almost the same as that of PTOS seek for short seeks and only slightly longer than that of the PTOS seek by around 2ms for long seeks. Therefore the loss in the seek time performance for the new algorithm is acceptable.

3.7 Summary

A systematic design method for a TDOF seeking controller to minimize the seeking acoustics in HDDs is proposed in this chapter. The acoustics level can be adjusted via seek design to make a tradeoff between the access time and the acoustics level. Both simulation and experimental results have shown that the acoustics in HDDs can be greatly reduced without the significant increase of the seeking time.

When HDDs with this seeking algorithm are used in some consumer devices, the noise generated by seeking during HDD read/write operations will be in a very low level and will not disturb the users when they play video/audio programmes; and as a result, the sound quality of the devices will be much improved.

Besides the acoustics improvement, vibration rejection of HDD servo systems is another topic that this research will address. When the external vibration is existing, the read/write operations of HDDs will be affected and normal video/audio flow will be disrupted. How to suppress the vibration in HDD servo systems will be discussed in the following chapters.

Figure 3.13: Sound Pressure Level Measurement in a Chamber

Figure 3.14: The seek time measurement

Chapter 4

Add-On Loop Gain Booster for Vibration Rejection

4.1 Introduction

HDDs in consumer devices need to perform well even when they are exposed to various external vibrations sources such as the jogging people and the speaker playing music. This request poses high requirement on the vibration rejection capability of HDD servo systems. A novel vibration rejection method is proposed in this chapter. This method has advantages over some conventional solutions. It is not model-based, so it is less sensitive to the variation of the plant parameters. It avoids obtaining disturbance observation by differentiating position signal. The vibration rejection in some frequencies can be improved without the compromise of the performance in other frequencies. It is an add-on scheme and the add-on

feature will be turned on only in specific vibration environment. The scheme comprises two parts: the vibration detection and the vibration compensation by the add-on feature. Two kinds of vibration detection are proposed: one uses the filtered vibration sensor output to detect the different vibrations and the other is a sensorless method to determine which kind of vibration is existing via the analysis of PES. The transient response caused by switching on/off the add-on feature is shortened by the reset control.

The block diagram of the whole system is shown in Fig. 4.1. The main control loop is composed of a state feedback controller and a current estimator. Besides the main control loop, there are two more parts for vibration handling: vibration detection and the add-on feature for vibration compensation. The part of vibration detection will determine whether the vibration is existing and which kind of vibration it is, and will accordingly decide whether to switch on/off the add-on feature. If the vibration is detected, the output of the add-on feature will be added to the output of the state feedback controller to form the final control input to the plant. If the vibration has gone, the add-on feature will be switched off by the vibration detection unit.

The chapter is organized as follows: in Section 4.2, two vibration detection methods are introduced and compared; the add-on feature is presented and the combined control law is derived in Section 4.3; Section 4.4 presents the application of the reset control to improve the transient response; simulation and experimental results are demonstrated in Section 4.6 and 4.7 respectively.

Figure 4.1: The Whole System

4.2 Vibration Detection

In order to switch on/off the add-on feature properly, we need to differentiate a specific vibration environment from the normal environment or the other kinds of vibration environments. Vibration detection can be achieved via two methods: 1. analysis of the vibration sensor output, as described in Section 4.2.1; 2. analysis of PES, as described in Section 4.2.2.

4.2.1 Vibration Detection via the Vibration Sensor

Most of HDDs have the vibration sensor to protect the data writing from the external vibrations; i.e., when the amplitude of external vibrations exceeds a pre-determined threshold, the data writing to the disc is stopped to prevent writing on the off-track position. The sampled vibration sensor output can be obtained through ADC. Different vibrations will impact the vibration sensor output in

different frequency bands, and thus the spectrum of the vibration sensor output can reflect the characteristics of the vibration and we can determine which kind of vibrations is residing through filtering the vibration sensor output in different bands. The method of vibration detection via the analysis of the vibration sensor output is shown in Fig. 4.2.

Figure 4.2: Vibration Detection via Shock Sensor

The selection of the Filter A is based on the spectrum of the disturbance sources. For example, based on the spectrum of the linear vibration in Fig. 1.4, a low-pass filter can be chosen to detect the linear vibration and the cut-off frequency of the low-pass filter is decided according to the frequency range where the linear vibration has impact. The Filter A can be represented by the second order IIR filter below:

$$\frac{f_{sensor}(z)}{S_{sensor}(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \quad (4.1)$$

where $S_{sensor}(z)$ is the vibration sensor output and $f_{sensor}(z)$ is the output of the Filter A. The power of $f_{sensor}(z)$ can then be obtained through the calculation of the mean square of $f_{sensor}(k)$ for N consecutive servo samples as follows.

$$P_{sensor} = \frac{1}{N} \sum_{k=1}^N f_{sensor}^2(k) \quad (4.2)$$

The value of P_{sensor} can reflect the level of linear vibrations. Table 4.1 demonstrates values of P_{sensor} with the scaling. The data is collected in a real HDD

Table 4.1: P_{sensor} in Different Environments

Vibration level (Grms)	$P_{sensor}/2^{12}$
0	0.28
1	37
2	122
3	387
Pink noise	1.5

in normal environment (0Grms vibration level), under different levels of linear vibrations and in pink noise environment. N is set as the number of servo sectors in one track. It can be seen that the differences of P_{sensor} in normal environment (0Grms) or pink noise environment as against in linear vibration environment are significant and we can easily tell whether the linear vibration is existing through reading the value of P_{sensor} ; hence the value of P_{sensor} can be used as the criterion to determine whether to switch on/off the add-on feature for linear vibration. To detect different vibrations, different filters will apply. For pink noise, a band-pass filter will be selected.

4.2.2 Vibration Detection via PES

To detect the external vibrations, we cannot directly use PES for analysis. PES can be separated into two components: RRO (repeatable run-out) and NRRO (non-repeatable run-out). RRO is locked to the spindle rotation in both frequency and phase and can be rejected by some servo control algorithms. NRRO comes from various disturbances and noise, such as internal and external vibrations, the measurement noise, computation truncation, etc. If PES is assumed to be ergodic

and the average of PES NRRO converges to be zero, PES RRO and NRRO can be calculated as in (4.3) and (4.4) with M revolutions of PES data.

$$PES_{RRO}(k) = \frac{1}{M} \sum_{i=1}^M PES_i(k) \quad (4.3)$$

$$PES_{NRRO}(k) = PES_i(k) - PES_{RRO}(k) \quad (4.4)$$

where k represents k th servo sample and i represents i th revolution. Different vibrations will impact PES NRRO in different frequency bands; namely, the spectrum of PES NRRO can reflect the characteristics of the vibration, therefore, we can determine which kind of vibrations is residing from the signature of PES NRRO spectrum. The method of vibration detection via the analysis of PES NRRO is shown in Fig. 4.3.

Figure 4.3: Vibration Detection Via PES

Same with Section 4.2.1, the selection of the Filter A is based on the spectrum of the disturbance sources. The same filter with 4.1 can be used:

$$\frac{f_{NRRO}(k)}{PES_{NRRO}(k)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}}$$

where $f_{NRRO}(k)$ is the output of the filter. Then calculate the mean square of $f_{NRRO}(k)$ for N consecutive servo samples as follows.

$$P_{NRRO} = \frac{1}{N} \sum_{k=1}^N f_{NRRO}^2(k) \quad (4.5)$$

Table 4.2: P_{NRRO} in Different Environments

Vibration level (Grms)	PES NRRO 1σ (percentage of track pitch)	P_{NRRO}
0	2.55	0.18
1	8.70	2.16
2	12.1	3.91
3	13.8	4.35
Pink noise	4.20	0.85

The value of P_{NRRO} can reflect the level of vibrations. Table 4.2 demonstrates values of P_{NRRO} collected in a real HDD under different levels of linear vibrations and in pink noise environment. N is set as the number of servo sectors in one track. It can be seen that the differences between P_{NRRO} in various environments are significant; hence the value of P_{NRRO} can also be used as the criterion to determine whether to switch on/off the add-on feature.

4.2.3 Comparison of Two Vibration Detection Methods

The method of vibration detection through analysis of vibration sensor output is simpler in implementation as it does not involve the calculation of PES NRRO, but it has the following disadvantages, compared with the method of vibration detection through analysis of PES NRRO.

1. Some HDDs do not have the vibration sensor or do not assign an dedicated ADC channel for vibration sensor output, then this method cannot be used or extra cost is needed;
2. The vibrations that need to be detected are those that will introduce dis-

turbances to the servo control system and therefore cause PES to become bigger than normal. Some vibrations may not have significant impact on PES, but generate a large vibration sensor output; in this case, the vibration detection via the vibration sensor output may falsely trigger the vibration compensation and PES will become worse.

4.3 The Add-on Loop Gain Booster Scheme

4.3.1 The Add-on Feature

The block diagram of the add-on feature is presented in Fig. 4.4.

Figure 4.4: The Block Diagram of the Add-on Feature

Filter B can be selected to be the same as Filter A. α is an adjustable gain for different degree of disturbance rejection. The function of the phase compensation filter is to compensate the phase loss caused by the filter B and maintain the system stability.

The output of Filter B, f_B , will be:

$$f_B(k) = \alpha \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} u_1(k)$$

where u_1 is the output of the state feedback controller.

The phase compensation filter can be chosen as a second-order IIR filter,

$$\frac{f_1(k)}{f_B(k)} = \frac{d_0 + d_1 z^{-1} + d_2 z^{-2}}{1 + c_1 z^{-1} + c_2 z^{-2}} \quad (4.6)$$

The transfer function from u_1 to the final control input, u , is

$$\frac{u(k)}{u_1(k)} = \left(1 + \alpha \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \frac{d_0 + d_1 z^{-1} + d_2 z^{-2}}{1 + c_1 z^{-1} + c_2 z^{-2}}\right) \quad (4.7)$$

and its state space representation is:

$$M(k) = FM(k-1) + Gu_1(k) \quad (4.8)$$

$$u(k) = NM(k) \quad (4.9)$$

where $F \in \mathbb{R}^{4 \times 4}$, $G \in \mathbb{R}^{4 \times 1}$ and $N \in \mathbb{R}^{1 \times 4}$ are constant matrixes and M is the state vector.

4.3.2 Combined Control Law

The same current estimator as (3.12) can be used, but the control law will be different with (3.13) because the controller in (3.13) is designed for seeking and

the control law here must be designed for tracking; the controller for tracking needs much higher bandwidth than that for seeking.

$$u_1(k) = -K_1 \hat{X}(k) \quad (4.10)$$

where K_1 is the gain matrix of the tracking controller. Taking the add-on feature into account, and substitute (4.9) into (3.12),

$$\hat{X}(k) = (\Phi - LH\Phi)\hat{X}(k-1) + (\Gamma - LH\Gamma)NM(k-1) + Ly(k) \quad (4.11)$$

Then substitute (3.12) and (4.10) into (4.8)

$$M(k) = -GK_1(\Phi - LH\Phi)\hat{X}(k-1) + [F - GK_1(\Gamma N - LH\Gamma N)M(k-1) - GK_1Ly(k)]$$

The state equation and the output equation of the whole controller will be:

$$\begin{bmatrix} \hat{X}(k) \\ M(k) \end{bmatrix} = \Phi_{xm} \begin{bmatrix} \hat{X}(k-1) \\ M(k-1) \end{bmatrix} + \Gamma_{xm}y(k) \quad (4.12)$$

$$u(k) = H_{xm} \begin{bmatrix} \hat{X}(k) \\ M(k) \end{bmatrix} \quad (4.13)$$

where

$$\Phi_{xm} = \begin{bmatrix} \Phi - LH\Phi & \Gamma N - LH\Gamma N \\ -GK_1(\Phi - LH\Phi) & F - GK_1(\Gamma N - LH\Gamma N) \end{bmatrix}$$

$$\Gamma_{xm} = \begin{bmatrix} LN \\ -GK_1L \end{bmatrix}$$

$$H_{xm} = [0 \quad N]$$

A comparison of equations (3.12) (4.10) with (4.12)(4.13) shows that the order of the controller has been increased by the add-on feature; and the new states are used to boost the controller gain in the disturbance frequency range and thus to improve the disturbance rejection in that frequency band. Thus the add-on scheme is essentially a loop gain booster over a selected frequency band.

4.4 Reset Control to Improve the Transient Response

When turning on/off the add-on feature, a transient response will occur and will cause large PES. A long transient is unacceptable. Reset control can help to reduce the transient response time.

A reset controller is a linear time-invariant system whose states, or subset of states, are reset to zero when the controller input is zero. One of the advantages of the reset control is that it can overcome the inherent limitations of linear feedback control, and it can meet the specification of rising time without overshooting [108],[109]. The reset control has already been used in HDD control for better seeking and tracking performance [111],[112].

The control system with a reset controller is shown in Fig. 4.5. The reset controller includes part of states of the baseline controller that need to be reset; and L includes all other states and the plant. The baseline linear controller is responsible for the system stability and performance. The objective of using the reset controller in this research is to break the limitation of the linear system and thus help to shorten the transient response.

Figure 4.5: Block Diagram Of Reset Control

The reset controller is described by the following impulsive differential equations:

$$\begin{aligned} \dot{x}_r(t) &= A_r x_r(t) + B_r e(t), \quad e(t) \neq 0 \\ x_r(t^+) &= A_{rs} x_r(t), \quad e(t) = 0 \\ u_r(t^+) &= C_r x_r(t), \quad e(t) = 0 \end{aligned} \tag{4.14}$$

where $x_r(t)$ is the reset controller state, t^+ is the resetting time, $A_r \in \mathbb{R}^{n_r \times n_r}$, $B_r \in \mathbb{R}^{n_r \times 1}$ and $C_r \in \mathbb{R}^{1 \times n_r}$ are constant matrixes. The matrix $A_{rs} \in \mathbb{R}^{n_r \times n_r}$ selects the states to be reset. Without loss of generality, $A_r = \begin{bmatrix} I_{\bar{d}} & 0 \\ 0 & 0_d \end{bmatrix}$ is assumed, where d is the number of states to reset among n_r controller states.

Assume that the linear part L is strictly proper and adopts the realization below:

$$\begin{aligned}\dot{x}_l(t) &= A_l x_l(t) + B_l u_r(t) \\ y(t) &= C_l x_l(t)\end{aligned}\tag{4.15}$$

where $A_l \in \Re^{n_l \times n_l}$, $B_l \in \Re^{n_l \times 1}$ and $C_l \in \Re^{1 \times n_l}$.

The closed-loop reset control system is

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Br(t), \quad e(t) \neq 0 \\ x_r(t^+) &= A_s x(t), \quad e(t) = 0 \\ y(t) &= Cx(t), \\ e(t) &= r(t) - Cx(t)\end{aligned}\tag{4.16}$$

where $x(t) = [x_l \ x_r]'$ and

$$\begin{aligned}A &= \begin{bmatrix} A_l & B_l C_r \\ -B_r C_l & A_r \end{bmatrix} \\ B &= \begin{bmatrix} 0 \\ B_r \end{bmatrix} \\ A_s &= \begin{bmatrix} I & 0 \\ 0 & A_{rs} \end{bmatrix} \\ C &= [C_l \ 0]\end{aligned}$$

In the absence of resetting, i.e., when $A_s = I$, the resulting close-loop system is just the base-linear system. The internal stability of the system (4.16) is

established in [109] by giving a necessary and sufficient condition (called the H_β -condition) on the base-linear system: there exists a $\beta \in \Re^d$ and a positive-definite $P_d \in \Re^{d \times d}$ such that

$$H_\beta(s) = [\beta C_l \quad 0_{\bar{d}} \quad P_d](sI - A)^{-1} \begin{bmatrix} 0 \\ 0'_{\bar{d}} \\ I_d \end{bmatrix} \quad (4.17)$$

is strictly positive real (SPR). The H_β -condition provides a theoretical solution of the testability of input-output stability for a reset control system. In digital implementation, due to sampling and quantization, the resetting time may not be at the precise moment when the input is zero. Nevertheless, the above stability condition requires no assumption on the evolution of resetting time [109]. The robustness to digital implementation errors of a reset system is discussed in [110]. The steady-state performance of reset control system is also addressed in [109] and the reset action will not degrade or affect the asymptotic tracking capability of the base-linear system. In this research, RIDE (Reset Integral-Derivative Element) [111] is adopted to form the reset controller. The reason why the RIDE is selected instead of the reset integrator or reset lag compensator [109],[113] is that the baseline controller has the derivative component, which will greatly amplify the sharp change in the output of the reset integrator or lag compensator. The discrete transfer function of the reset element is

$$G_R(z) = \frac{Z + Z_r}{Z(Z - 1)} \quad (4.18)$$

The corresponding reset controller in state space form is:

$$\begin{aligned} x(k+1) &= \Phi_r x(k) + \Gamma e(k), \quad |e(k)| > \delta \\ x(k^*) &= 0, \quad |e(k)| \leq \delta \\ u(k) &= H_r x(k) \end{aligned} \tag{4.19}$$

where Φ_r , Γ_r and H_r are converted from (4.18); $e(k)$ is PES in sample k ; and δ is a small positive value; it is not equal to zero because the input is seldom to be zero in sampled system.

4.5 The Overall Control System

The overall control system that can handle both the linear vibration and the pink noise is demonstrated in Fig. 4.6. The vibration detection unit will determine which kind of vibration environment the drive is residing in and accordingly switch on/off the corresponding add-on feature and RIDE. At one time, only one add-on feature or RIDE will be switched on.

4.6 Simulation Results

4.6.1 Vibration Detection

As discussed in Section 4.2.2, the selection of Filter A is based on the spectrum of vibration sources. The spectrums of the linear vibration and pink noise can be found in Figs. 1.4 and 1.5.

Figure 4.6: The Overall Control System

To handle the linear vibration, a low-pass filter is chosen. With the sampling period to be 3.3407e-005 second, the coefficients in the (4.1) are set as follow:

$$\frac{f_{sensor}(k)}{S_{sensor}(k)} = \frac{0.00209 + 0.004179z^{-1} + 0.00209z^{-2}}{1 - 1.867z^{-1} + 0.875z^{-2}} \quad (4.20)$$

The frequency response of Filter A is presented in Fig. 4.7. The cut-off frequency is around 450Hz.

Figure 4.7: Low-pass Filter for Linear Vibration

To handle the pink noise, a 4th order band pass filter is needed. The coefficients are set as follow:

$$\frac{f_{sensor}(k)}{S_{sensor}(k)} = \frac{0.001663 - 0.003326z^{-2} + 0.001663z^{-4}}{1 - 3.843z^{-1} + 5.577z^{-2} - 3.621z^{-3} + 0.888z^{-4}} \quad (4.21)$$

The corresponding frequency response of the Filter A is presented in Fig. 4.8.

The filter is a typical band pass filter and the cut-off frequency is around 500Hz and 1000Hz.

Figure 4.8: Band Pass Filter for Linear Vibration

4.6.2 The Add-on Feature

Linear Vibration

For linear vibration, the frequency response of the baseline controller without the add-on feature (4.10) and the frequency response of the controller with the add-on feature (4.12) (4.13) are compared in Fig. 4.9. α in (4.7) is set at 1. It shows in the magnitude plot that the controller gain has been increased by around 5dB in low frequency range (0-500Hz) with the add-on feature.

Figure 4.9: Controller for Linear Vibration

The comparison of the sensitivity function can be found in Fig. 4.10. It can be seen that the controller with the add-on feature has better disturbance rejection in the frequency range 0-500Hz and therefore works better than the original controller under linear vibration.

α in (4.7) is an adjustable gain for different degree of vibration rejection. The controller responses in Fig. 4.11 present the effect of α : bigger α produces bigger controller gain and greater vibration rejection in the frequency range 0-500Hz.

Figure 4.10: Sensitivity Function for Linear Vibration

Pink Noise

For pink noise, the frequency response of the baseline controller without the add-on feature (4.10) and with the feature (4.12) (4.13) are compared in Fig. 4.12. It illustrates that the controller gain has been increased by around 5dB in the frequency range from 500Hz to 1000Hz with the add-on feature.

The comparison of the sensitivity function can be found in Fig. 4.13. It can be seen that the controller with the add-on feature has better disturbance rejection in the frequency range 500-1000Hz and therefore works better than the original controller under pink noise.

In Fig. 4.13, α is set at 0.8. To achieve greater vibration attenuation, an even

Figure 4.11: Controller Response for different α

bigger α can be used; but when $\alpha > 0.9$, the stability margin of the system is not big enough and the control loop may become unstable. The phase compensation filter (4.6) can help maintain the system stability. The filter coefficients are shown below:

$$\frac{f_{sensor}(k)}{S_{sensor}(k)} = \frac{0.969 - 1.678z^{-1} + 0.730z^{-2}}{1 - 1.676z^{-1} + 0.706z^{-2}} \quad (4.22)$$

The frequency response of the phase compensation filter is presented in Fig. 4.14. Phase gain is achieved in low frequency range to compensate the phase loss caused by the add-on feature and thus helps maintain the system stability.

The effect of the phase compensation filter is illustrated in Fig. 4.15. When big α is used, the peak of the sensitivity function reaches 12dB and the stability margin is small. The phase compensation filter increases the stability margin

Figure 4.12: Controller for Pink Noise

and the trade-off is that the disturbance rejection in low frequency is reduced. The selection of α is a trial-and-error procedure to achieve a balance between the stability margin and vibration attenuation.

It can be seen from above that the design of the add-on feature is determined by the nature of the disturbance source and does not depend on an accurate plant model. As a result, the scheme is not sensitive to the variation of the plant parameters provided that the system stability be maintained.

Figure 4.13: Sensitivity Function for Pink Noise

4.7 Experimental Results

4.7.1 Experimental Setup

The experiment was conducted in a commercially available 2.5- inch Seagate drive with rpm = 7200, TPI=310k and the sampling frequency = 29.9kHz. The vibration detection method used in the experiment was the one via PES. The code with the algorithm was downloaded to the drive.

The sensitivity function was obtained first in real drive. Then PES was measured in two kinds of vibration tests:

Linear vibration test. The drive was installed on a linear shaker for testing;

Figure 4.14: Phase Compensation Filter

Pink noise test. The drive was placed into a laptop computer, which was playing the pink noise sound during testing.

4.7.2 Sensitivity Function

Sensitivity function is a good measure of disturbance rejection capability. The sensitivity function of the baseline controller is designed for better PES in normal environment. To have a better performance under linear vibration, the sensitivity function should have greater attenuation in low frequency, as shown in Fig. 4.10; while the sensitivity function for pink noise should have greater attenuation in the frequency range 500-1000Hz, as shown in Fig. 4.13. Through the vibration

Figure 4.15: The Effect of Phase Compensation Filter

detection scheme to turn on/off the proper add-on feature, for different vibration environments, the corresponding sensitivity function can be applied to HDD servo control systems.

The method of measuring the sensitivity function is illustrated in Fig. 4.16. A sweeping sinusoidal wave from 100Hz to the nyquist frequency with flat amplitude is used as the disturbance d to be injected into the loop and the response is PES. The sensitivity function S can be calculated with the equation below:

$$S = \frac{DFT(PES)}{DFT(d)} \quad (4.23)$$

When the sinusoidal wave is sweeping in low frequency range (0-500Hz), it will

Figure 4.16: Method to Measure The Sensitivity Function

enable the add-on feature for linear vibration; in middle frequencies (500-1000Hz), it will trigger the add-on feature for pink noise; in other frequency ranges, neither of the add-on features is activated; as a result, the whole measured sensitivity function will have greater attenuation in both the low and middle frequency ranges while maintaining the same with original sensitivity function in other frequency range. It looks as if the water-bed effect had been 'avoided', which is shown in Fig. 4.17. 500Hz is the switching point between the add-on feature for linear vibration and the one for pink noise, and therefore the discontinuity at 500Hz in the sensitivity function can be seen. The measured sensitivity function indicates the advantage of this scheme over the conventional loop shaping scheme. For loop shaping scheme, if the controller is designed for linear vibration, more attenuation in 0-500Hz is needed in the sensitivity function, but amplification in other frequency ranges is unavoidable; if the controller is designed for pink noise, more attenuation in 500-1000Hz should be achieved, but amplification in 0-500Hz or other frequency ranges will be seen. For the proposed scheme, better disturbance rejection is achieved in a wide frequency range and the performance in other frequencies is not sacrificed.

It is noteworthy that if the method of vibration detection via the vibration sen-

Figure 4.17: Sensitivity Function Measurement

sor is used, we cannot get such a sensitivity function measurement because the injected sweeping sinusoidal wave has little effect on the vibration sensor output and thus will not enable any add-on feature.

4.7.3 PES Improvement

To perform a standard linear vibration test, the HDD was mounted vertically onto a linear shaker, as shown in Fig. 4.18. A signal with flat amplitude, random frequencies 0-500Hz was used to drive the shaker. Through setting a proper threshold for P_{sensor} , the add-on feature will be switched on when the vibration amplitude is greater than 0.5Grms and will be switched off when the vibration

amplitude is less than 0.5Grms.

Figure 4.18: Linear Vibration Test on a Linear Shaker

Fig. 4.19 illustrates the PES improvement by the add-on feature when the vibration amplitude is equal to 2Grms. The add-on feature for the linear vibration is enabled by the vibration detection, so the sensitivity function in Fig. 4.10 is applied. The upper half of the Fig. 4.19 presents PES response in time domain and the lower half shows the PES in frequency domain. It can be seen that the linear vibration generates large disturbance in 0-500Hz and the add-on feature

suppresses the disturbances successfully and achieves 35% reduction in PES 1σ value.

Figure 4.19: PES in Linear Vibration Test

The drive was then assembled into a laptop computer, as shown in Fig. 4.20. PES was measured when the laptop was playing pink noise sound with the speaker volume set to be full. The PES measurement is shown in Fig. 4.21. The add-on feature for the pink noise is enabled by the vibration detection in pink noise environment, so the sensitivity function in Fig. 4.13 is applied. As a result, PES is improved greatly in pink noise frequencies and 1σ value of PES is reduced by 23%.

Figure 4.20: HDD in Laptop

4.7.4 Transient Responses

For the HDD plant in this experiment, Z_r in (4.18) is equal to -0.9225, and δ in (4.19) is set at 0.8% of the track pitch. RIDE will only be switched on at the moment when the add-on feature is turned on or off, and it will be switched off after the transient has gone. Fig. 4.22 presents the improvement of the transient response by RIDE when the add-on feature has been turned on at servo sample 100. It tells that the duration of the transient response is reduced by 40%.

4.8 Summary

The proposed method can suppress the disturbance induced by the linear vibration and pink noise without the compromise of the performance in other environments. The experiments produce satisfactory results. The method can be

Figure 4.21: PES in Pink Noise

extended to handle various vibration sources easily via different filter designs of the add-on feature; and the filter design can be based on the characteristics of the disturbance spectrum.

The algorithm in this chapter can handle various external vibrations with low amplitude, such as vibrations induced by the speaker when playing music, or people jogging or cycling, so HDDs with this algorithm are capable of maintaining the smooth data transfer of the consumer devices under such vibrations. The algorithm, however, has difficulty in suppressing the vibrations with large amplitude because it is essentially a linear loop shaping method and can only get limited attenuation on the disturbance due to the stability requirement. To handle vibrations with large amplitude that the consumer devices may encounter,

Figure 4.22: Improvement of the transient response by RIDE

vibration sensor-based feedforward algorithm is a proper solution, which will be discussed in the following chapters.

Chapter 5

Adaptive Filtering-Based Acceleration Feedforward Control for Vibration Rejection

5.1 Introduction

For linear or rotational vibration with large amplitude (3rads/s^2 or higher), all the linear loop shaping methods mentioned earlier, including the method in Chapter 4, cannot obtain enough attenuation in the control loop; consequently PES will become very large and the drive performance will be degraded greatly. As a result, read/write operations of HDDs will become very slow and smooth flow of video/audio programmes of consumer devices will be broken. Vibration sensor-based feedforward algorithm is a proper solution to the problem. The effect of the

vibration on the position error is actively minimized by feeding the accelerometer signal in some form into a feedforward control loop. This feedforward compensation is outside the main control loop therefore the water-bed effect will not apply.

This chapter is organized as follows: Section 5.2 describes accelerometer-based feedforward control. Section 5.3 introduces the accelerometer that is used in this research. In Section 5.4, two kinds of the adaptive filtering algorithms are introduced: LMS and RLS. Section 5.5 presents the Filtered-X algorithm.

5.2 Accelerometer-Based Feedforward Control

The block diagram of the whole feedforward control is presented in Fig 5.1. C represents the baseline controller of the main loop and P represents the HDD plant. The accelerometer output goes through an adaptive filter and the filter output is feedforwarded into the main control loop to cancel the disturbance d that is caused by the vibration. The coefficients of the adaptive filter is adapted by the adaptive filtering algorithm. The Filtered-X algorithm is introduced between the accelerometer output and the adaptive filtering algorithm.

5.3 Introduction to the Accelerometer

An accelerometer is one of the many types of sensors. In this case, the physical property being measured is the acceleration. The acceleration is defined as the

Figure 5.1: Block Diagram for The Whole System

rate of change of velocity of an object. The acceleration can be linear in a linear vibration environment or angular in a rotational vibration environment.

Known rotation sensors are expensive for HDD application. In this research, two linear accelerometers are used to sense both the linear vibration and rotational vibration [114]. As shown in Fig. 5.2, two linear accelerometers that are spaced from each other by a predetermined distance are placed parallel, with opposite polarity, on the PCB of the HDD. The relevant linear acceleration is in the direction perpendicular to tracks on the x-y plane, and the two accelerometers are arranged to pick up that component in the most sensitive orientation. Then the linear acceleration and rotational acceleration can be obtained by (5.1) and (5.2).

$$A_L = \frac{LA_1 + LA_2}{2} \quad (5.1)$$

$$A_R = \frac{LA_1 - LA_2}{2} \quad (5.2)$$

where

A_L : linear acceleration

A_R : rotational acceleration

LA_1, LA_2 : the outputs of the linear accelerometers 1 and 2 respectively.

Figure 5.2: Two Linear Accelerometers in PCBA

The sensed rotation is independent of the location of the axis about which the HDD rotates, and the radius of rotation. The accelerometers produce equal outputs in response to translational movement of the HDD. Since the rotation is computed as a function of the difference between the outputs of the linear accelerometers, the net effect of translational movement of the HDD is zero and the sensor output reflects only rotational movement.

There are many types of accelerometers. Piezoelectric shock sensor is selected in this research. Piezoelectric accelerometer is one of the most commonly-used

types. Piezoelectric accelerometer consists of a mass and a piezoelectric component. When the accelerometer is subjected to acceleration, the mass pushes against the piezoelectric element, and the piezoelectric element then produces a voltage that is proportional to the acceleration of an impact or a vibration to which it is exposed. The shock sensor utilizes piezoelectric ceramics to convert the energy of impact into a proportional electrical signal. The sensor, featuring compact and lightweight design, is suitable for the application requiring vibration sensing [115].

5.4 Adaptive Filtering Algorithms

An adaptive filter has an adaption algorithm, which is meant to monitor the environment and to vary the filter transfer function accordingly. The algorithm starts from a set of initial conditions, which may correspond to complete ignorance about the environment, and, based on the actual signals received, attempts to find the filter design that is optimum in some sense. In a stationary environment, the filter is expected to converge to the wiener filter. In a nonstationary environment, the filter is expected to track time variations and to adjust its filters coefficients accordingly [116]-[118].

As a result, there is no such a thing as a unique optimal solution to the adaptive filtering problem. Adaptive filters have to do without a priori statistical information, but instead usually have to draw all their information from only one given realization of the process, namely one sequence of time samples. There are, however, many options as to what information is extracted, how it is gathered,

and how it is used in the algorithm. Given only one realization of the process, the adaptation algorithm will have to operate with instantaneous estimates of the signal statistics. Again, such estimates may be obtained in various ways. As such, we have more than one solution, which results in a variety of algorithms. Each alternative algorithm offers desirable features of its own.

The basic operations of the adaptive filtering involves two processes:

1. A filtering process, which produces an output signal in response to a given input signal;
2. An adaptation process, which aims to adjust the filter parameters (filter transfer function) to the environment. The adaptation is steered by an error signal that indicates how well the filter output matches some desired response.

A prototype adaptive filtering scheme is depicted in Fig. 5.3.

Figure 5.3: Adaptive Filtering Prototype

Normally the adaptive filter can be selected as either a FIR filter or a IIR filter. The choice of FIR filter leads to tractable mathematics and fairly simple algorithms; the resulting filter is unconditionally stable. IIR filter, however, involves more computation and often leads to stability problem [116]. In this research, we concentrate on the adaptive FIR filter algorithms. The output of a FIR filter is a linear combination of N delayed filter input samples, as shown in Fig. 5.4.

Figure 5.4: Structure of FIR Filters

The aim of the adaptation is to adapt the weight w_i so that the error is minimized. Normally the adaptation scheme will take the form

$$\mathbf{w}(n) = \mathbf{w}(n-1) + (\text{correction}) \quad (5.3)$$

where $\mathbf{w}^T(n) = [w_0(n) \ w_1(n) \ \cdots \ w_{N-1}(n)]$ contains the tap weights at time n .

The error signal is normally used to steer the adaptation, and so we have

$$\mathbf{w}(n) = \mathbf{w}(n-1) + (d(n) - \mathbf{u}^T(n)\mathbf{w}(n-1))\Delta \quad (5.4)$$

where $d(n)$ is the desired signal and $\mathbf{u}(n)$ is the input signal. Δ is a correction vector for which different adaptive filtering schemes have different choices and

its role is to specify which direction the algorithm should move from $\mathbf{w}(n-1)$ to $\mathbf{w}(n)$. The way of the weights adaptation is determined by how the error is minimized, i.e., what kind of cost function will be chosen.

5.4.1 Cost Functions

Normally the quadratic cost functions are selected as the cost function in that they can lead to linear optimization problems [119].

A popular cost function, referred to as the mean-squared error (MSE) criterion, is defined as the mean-square value of the estimation error, i.e., the mean-square value of the difference between the desired response and the actual filter output

$$\begin{aligned} J_{MSE} &= E[e(n)^2] \\ &= E[|d(n) - y(n)|^2] \end{aligned} \tag{5.5}$$

where $E[\cdot]$ is the expectation operator, $e(n)$ is the error signal and $y(n)$ is the filter output at time n . For FIR filter,

$$J_{MSE} = E[|d(n) - \mathbf{w}(n)^T \mathbf{u}(n)|^2] \tag{5.6}$$

The cost function above is probabilistic in nature, for it involves the expectation operator $E[\cdot]$. In such a probabilistic framework, all signals are viewed as realizations of stochastic processes. As we shall see later, this means that certain statistical information (auto-correlations and cross-correlations) has to be available in order to design the filter. In most applications, however, only data

sequences are given, i.e., only one realization of the processes is involved. If instantaneous estimates are substituted for the statistical parameters, it will lead to the so-called LMS algorithm, as shown in Section 5.4.2.

Alternatively, one can replace the mean-squared error cost function with a time-averaged squared error, also referred to as a least squares (LS) error criterion,

$$J_{LSE} = \frac{1}{N} \sum_{n=1}^N |d(n) - \mathbf{w}(n)^T \mathbf{u}(n)|^2 \quad (5.7)$$

which is no longer probabilistic, but works directly with the given data samples. This direct approach can produce comparable results without having to rely on all the probabilistic machinery. In particular, this leads to the RLS procedure, as seen in Section 5.4.3.

5.4.2 Standard LMS Estimation

In a simple form of iterative descent known as the method of steepest descent, the successive adjustments applied to the weight vector $\mathbf{w}$ are in the direction of steepest descent, that is, in a direction opposite to the gradient vector of the cost function J [121], which is denoted by ∇J ,

$$\nabla J = \frac{\partial J}{\partial w} \quad (5.8)$$

Accordingly, the steepest-descent algorithm is formally described as

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu \nabla J \quad (5.9)$$

where μ is a positive constant called the step-size parameter.

Let us recall the cost function of LMS,

$$J_{MSE} = E[e(n)^2]$$

and

$$e(n) = d(n) - \sum_{m=0}^M w_m u(n-m)$$

The gradient vector will be

$$\begin{aligned} \nabla J &= \frac{\partial J}{\partial \mathbf{w}} \\ &= \frac{\partial E[e(n)^2]}{\partial \mathbf{w}} \\ &= 2E\left[\frac{\partial e(n)}{\partial \mathbf{w}} e(n)\right] \\ &= -2E[\mathbf{u}(n)e(n)] \\ &= -2E\left[\mathbf{u}(n)\left(d(n) - \sum_{m=0}^M w_m u(n-m)\right)\right] \\ &= -2E[\mathbf{u}(n)d(n)] + 2 \sum_{m=0}^M w_m E[\mathbf{u}(n)\mathbf{u}(n-m)] \\ &= -2\mathbf{t} + 2\mathbf{R}\mathbf{w} \end{aligned} \tag{5.10}$$

where

$\mathbf{t} = E[\mathbf{u}(n)d(n)]$ is the cross-correlation vector between the input vector $\mathbf{u}$ and the desired response d ;

$\mathbf{R} = E[\mathbf{u}(n)\mathbf{u}(n-m)]$ is the auto-correlation matrix of the input vector $\mathbf{u}$.

If it were possible to make exact measurements of the gradient vector ∇J at each iteration, and the step-size parameter μ is suitably chosen, the weights computed via the steepest-descent algorithm (5.9) would indeed converge to the optimum Wiener solution. In reality, however, exact measurements of the gradient vector are impossible, as it would require prior knowledge of both the auto-correlation matrix of the inputs and the cross-correlation matrix between the inputs and the desired response. Consequently, the gradient vector must be estimated from the available data when we operate in an unknown environment. The simplest choice of estimation is to use instantaneous estimates for $\mathbf{R}$ and $\mathbf{t}$ that are based on sample values of the input vector and desired response, as defined below,

$$\hat{\mathbf{R}}(n) = \mathbf{u}(n)\mathbf{u}(n)^T$$

and

$$\hat{\mathbf{t}}(n) = \mathbf{u}(n)d(n)$$

The corresponding instantaneous estimate of the gradient vector is

$$\hat{\nabla} J(n) = -2\mathbf{u}(n)d(n) + 2\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) \quad (5.11)$$

Substituting the estimate of (5.11) for the gradient vector ∇J in the steepest-descent algorithm described in (5.9), we get a new recursive relation for updating the weight vector:

$$\begin{aligned}
\mathbf{w}(n+1) &= \mathbf{w}(n) - \mu[-2\mathbf{u}(n)d(n) + 2\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n)] \\
&= \mathbf{w}(n) + 2\mu\mathbf{u}(n)[d(n) - \mathbf{u}^T(n)\mathbf{w}(n)]
\end{aligned} \tag{5.12}$$

Then the whole adaptive algorithm can be described with three equations below:

1. Adaptive filter:

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \tag{5.13}$$

2. Estimation error:

$$e(n) = d(n) - y(n) \tag{5.14}$$

3. Weight adaptation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu\mathbf{u}(n)e(n) \tag{5.15}$$

The algorithm described from (5.13) to (5.15) is just the adaptive LMS algorithm. At each iteration or time update, this algorithm requires knowledge of the most recent data of $\mathbf{u}(n)$, $d(n)$ and $\mathbf{w}(n)$. The iterative procedure is started with an initial guess $\mathbf{w}(0)$.

The instantaneous estimates of R and t have relatively large variances. At the first sight, it may, therefore, seem that the LMS algorithm is incapable of performing well, since the algorithm uses these instantaneous estimates. We must remember, however, that the LMS algorithm is recursive in nature, with the result that the algorithm itself can effectively average these estimates, in some sense, during the course of adaptation.

The step size parameter μ plays a critical role in the convergence of LMS. To guarantee convergence of the weights, μ must be chosen in the range [122].

$$0 < \mu < \frac{1}{\text{tr}[R]} \quad (5.16)$$

where $\text{tr}[R]$ is the trace of the auto-correlation maxtrix of R .

The upper bound obtained for the value of μ is important from the practical point of view, because it gives us an indication of the maximum value of μ that can be used in order to achieve convergence of the coefficients. In most cases, the value of μ should not be chosen close to the upper bound.

5.4.3 Standard Least Square Estimation

It is assumed that we need to design a FIR filter to achieve a desired filter response. The filter is fed by an input vector $\mathbf{u}(k)$ and the corresponding desired response sequence is $d(k)$. The error signal $e(k)$ is

$$e(k) = d(k) - \mathbf{w}(k)^T \mathbf{u}(k) \quad (5.17)$$

where $\mathbf{w}(k)$ is the filter coefficient vector.

The objective of the filter design is to minimize the error e , so a cost function is

selected as:

$$\begin{aligned}
 J_{LSE}(m) &= \sum_{k=1}^m e(k)^2 \\
 &= \sum_{k=1}^m (d(k) - \mathbf{w}^T \mathbf{u}(k))^2 \\
 &= \mathbf{D}^T \mathbf{D} - 2\mathbf{w}^T \mathbf{x}_{du} + \mathbf{w}^T \mathbf{X}_{uu} \mathbf{w}
 \end{aligned} \tag{5.18}$$

where

$$\begin{aligned}
 \mathbf{D} &= [d(1) \ d(2) \ \cdots \ d(m)]^T \\
 \mathbf{x}_{du}(m) &= \sum_{k=1}^m \mathbf{u}(k) d(k) \\
 \mathbf{X}_{uu}(m) &= \sum_{k=1}^m \mathbf{u}(k) \mathbf{u}^T(k)
 \end{aligned}$$

This is known as the least square criterion. The filter design problem becomes a problem of how to find the minimum of the cost function. The minimum of the cost function is located by setting the gradient equal to zero,

$$\begin{aligned}
 0 &= \frac{\partial J_{LS}}{\partial \mathbf{w}} \\
 &= \frac{\partial}{\partial \mathbf{w}} (\mathbf{D}^T \mathbf{D} - 2\mathbf{w}^T \mathbf{x}_{du} + \mathbf{w}^T \mathbf{X}_{uu} \mathbf{w}) \\
 &= 2\mathbf{X}_{uu} \mathbf{w} - 2\mathbf{x}_{du}
 \end{aligned} \tag{5.19}$$

Therefore the coefficient vector under least square estimation, $\mathbf{w}_{LS}$, can be obtained:

$$\mathbf{w}_{LS} = \mathbf{X}_{uu}^{-1} \mathbf{x}_{du} \tag{5.20}$$

Because

$$\mathbf{X}_{uu}(m) = \mathbf{X}_{uu}(m-1) + \mathbf{u}(m) \mathbf{u}^T(m) \tag{5.21}$$

$$\mathbf{x}_{du}(m) = \mathbf{x}_{du}(m-1) + \mathbf{u}(m)d(m) \quad (5.22)$$

it follows that

$$\begin{aligned} \mathbf{w}_{LS}(m) &= \mathbf{X}_{uu}^{-1}(m)\mathbf{x}_{du}(m) \\ &= \mathbf{X}_{uu}^{-1}(m)[\mathbf{x}_{du}(m-1) + \mathbf{u}(m)d(m)] \\ &= \mathbf{X}_{uu}^{-1}(m)[\mathbf{X}_{uu}(m-1)\mathbf{w}_{LS}(m-1) + \mathbf{u}(m)d(m)] \\ &= \mathbf{X}_{uu}^{-1}(m)[\mathbf{X}_{uu}(m) - \mathbf{u}(m)\mathbf{u}^T(m)]\mathbf{w}_{LS}(m-1) + \mathbf{u}(m)d(m) \\ &= \mathbf{w}_{LS}(m-1) + \mathbf{X}_{uu}(m)^{-1}\mathbf{u}(m)[d(m) - \mathbf{u}^T(m)\mathbf{w}_{LS}(m-1)] \end{aligned} \quad (5.23)$$

To avoid the calculation of inverse matrix, the well-known matrix inversion lemma (5.24) [121] needs to be applied.

$$[\mathbf{A} + \mathbf{BCD}]^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{B}[\mathbf{DA}^{-1}\mathbf{B} + \mathbf{C}]^{-1}\mathbf{DA}^{-1} \quad (5.24)$$

Define $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ in (5.24) as

$$\mathbf{A} = \mathbf{X}_{uu}(m-1)$$

$$\mathbf{B} = \mathbf{u}(m)$$

$$\mathbf{C} = \mathbf{I}$$

$$\mathbf{D} = \mathbf{u}^T(m)$$

Substituting the above definitions into (5.24) gives that

$$\begin{aligned} (\mathbf{X}_{uu}(m-1) + \mathbf{u}(m)\mathbf{u}^T(m))^{-1} &= \mathbf{X}_{uu}^{-1}(m-1) \\ &\quad - \mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m) \left((\mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m) + 1) \right)^{-1} \mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1) \end{aligned} \quad (5.25)$$

and therefore

$$\mathbf{X}_{uu}^{-1}(m) = \mathbf{X}_{uu}^{-1}(m-1) - \frac{\mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m)\mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1)}{1 + \mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m)} \quad (5.26)$$

Defining

$$\mathbf{P}(m) = \mathbf{X}_{uu}^{-1}(m)$$

gives that

$$\mathbf{P}(m) = \mathbf{P}(m-1) - \frac{\mathbf{P}(m-1)\mathbf{u}(m)\mathbf{u}^T(m)\mathbf{P}(m-1)}{1 + \mathbf{u}^T(m)\mathbf{P}(m-1)\mathbf{u}(m)} \quad (5.27)$$

Then the whole adaptive algorithm can be described with three equations below:

1. Adaptive filter:

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n)$$

2. Estimation error:

$$e(n) = d(n) - y(n)$$

3. Weight adaptation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{P}(n)\mathbf{u}(n)e(n) \quad (5.28)$$

$$\mathbf{P}(n) = \mathbf{P}(n-1) - \frac{\mathbf{P}(n-1)\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{P}(n-1)}{1 + \mathbf{u}^T(n)\mathbf{P}(n-1)\mathbf{u}(n)} \quad (5.29)$$

The coefficients of the adaptive filter are updated by the weight adaptation law; and the weight adaptation is performed based on the estimation error and the

input of the adaptive filter.

5.4.4 Evaluation of Adaptive Filtering Algorithms

In the evaluation of different adaptive filtering algorithms, several factors are normally taken into consideration [116]-[121]:

- **Rate of Convergence:** This is defined as the number of iterations required for the algorithm to converge. Many of the applications operate in unknown environments, so the speed of convergence is crucial.
- **Algorithm complexity:** Here the issues of concern include (a) the number of operations (i.e., multiplications, divisions, and additions/subtractions) required to make one complete iteration of the algorithm, (b) the size of memory locations required to store the data and the program.
- **Misadjustment:** This parameter provides a quantitative measure of the amount by which the final value of the mean-square error, averaged over an ensemble of adaptive filters, deviates from the minimum mean-square error produced by the Wiener filter.
- **Numerical stability:** In the implementation of the adaptive filtering algorithms, inaccuracies are generated due to quantization errors in internal calculations. In many applications, adaptive filter algorithms are operated over a long period of time, corresponding to millions of iterations. The algorithm is expected to remain stable all the time, and hence numerical issues are crucial to proper operation.

5.5 Filtered-X Algorithm

Figure 5.5: The System with Vibration Disturbance

Fig. 5.5 introduces how the vibration affects a control system with the accelerometer. The vibration source V generates an input disturbance D into the control loop and at the same time impacts the accelerometer output S . G_1 is the transfer function from the vibration source to the accelerometer and G_2 is the transfer function from the vibration source to the input disturbance. Therefore the relationships as below are straightforward:

$$S = G_1 V$$

$$D = G_2 V$$

Thus

$$D = \frac{G_2}{G_1} S \quad (5.30)$$

The effect of the input disturbance D on PES is:

$$PES_D = \frac{P}{1 + PC} D \quad (5.31)$$

where PES_D represents the position error induced by the input disturbance.

Thus the transfer function from the accelerometer to PES will be:

$$PES_D = \frac{P}{1 + PC} \frac{G_2}{G_1} S \quad (5.32)$$

$\frac{G_2}{G_1}$ is the transfer function that needs to be estimated through adaptive filtering. This is an active control application for the adaptive filtering. Unlike the most common application of the adaptive filtering such as electrical noise canceling where the filter output is an estimate of a desired signal and the error is just the difference of the filter output and the desired signal, in the active control application, the filter output will be used to activate a dynamic system and the error is the difference of the desired signal and the output signal of the dynamic system.

However, the adaptive filtering algorithm is likely to be unstable in this active control applications on the dynamic system due to the phase shift introduced by the forward path of the dynamic system [123]-[125]. A model of the dynamic system, $\hat{P}$, is introduced between the accelerometer output and the RLS algorithm to help stabilize the system [126],[127],

$$\hat{P} = \frac{P}{1 + PC} \quad (5.33)$$

$\hat{P}$ is called Filtered-X filter.

5.6 Summary

In this chapter, the accelerometer-based feedforward control to suppress the vibration is described and the accelerometer used in this research is introduced. Adaptive filtering methods are selected for feedforward control. Two kinds of the adaptive filtering algorithms, LMS and RLS, are introduced. When adaptive filtering is used for active control applications, Filtered-X algorithm is often deployed. How the Filtered-X algorithm will be used in this research is presented.

Two adaptive filtering-based algorithms will be studied in subsequent chapters: Leaky Normalized Filtered-X LMS in Chapter 6 and Weighted QRD-based Filtered-X RLS in Chapter 7.

Chapter 6

Vibration Rejection by Leaky Normalized Filtered-X LMS

6.1 Introduction

When the adaptive filtering algorithm is used in active control applications such as HDD servo control, the Filtered-X algorithm will help maintain the stability of the adaptive filtering algorithm. The normalized LMS algorithm will make LMS algorithm be more robust with respect to power variations of the input vector and increase the convergence speed of the LMS algorithm. The leaky LMS can help mitigate the problem of accumulated quantization error in implementation.

The chapter is organized as follows: in Section 6.2, the Filtered-X LMS algorithm is derived; the normalized LMS and the leaky LMS are described in Section 6.3 and Section 6.4 respectively; Section 6.5 summarizes the Leaky Normalized

Filtered-X LMS algorithm. Simulation method and simulation results are given in Section 6.6. Implementation and experimentation are demonstrated in Section 6.7.

6.2 Filtered-X LMS

The Filtered-X LMS algorithm is an adaptive filter algorithm that is suitable for active control applications. Fig. 6.1 shows the HDD servo system with the feedforward of an adaptive filter output and the filter coefficients are adapted by Filtered-X LMS algorithm. Take note that the error signal, PES, is no longer the

Figure 6.1: LMS in HDDs

difference between the desired response and the filter output in (5.14). The filter output goes through the HDD plant and the error is the difference between the desired response and the plant output, as described below:

$$e(n) = d(n) - \sum_{i=0}^{I-1} f_i y(n-i) \quad (6.1)$$

Here we assume that the plant of the HDD can be represented by a FIR filter with the coefficient vector $\mathbf{f} = [f_0 \ f_1 \ \cdots \ f_{I-1}]$. $y(n)$ is the filter output.

Substitute (5.13) into the above equation

$$e(n) = d(n) - \sum_{i=0}^{I-1} f_i \sum_{m=0}^{M-1} w_m(n-i)u(n-i-m) \quad (6.2)$$

Let us recall the cost function of LMS,

$$J_{MSE} = E[e(n)^2]$$

The gradient vector will be

$$\begin{aligned} \nabla J_f &= \frac{\partial J_f}{\partial \mathbf{w}} \\ &= \frac{\partial E[e(n)^2]}{\partial \mathbf{w}} \\ &= 2E\left[\frac{\partial e(n)}{\partial \mathbf{w}} e(n)\right] \quad (6.3) \\ &= 2E\left[\frac{\partial [d(n) - \sum_{i=0}^{I-1} f_i \sum_{m=0}^{M-1} w_m(n-i)u(n-i-m)]}{\partial w} e(n)\right] \\ &= -2E[\mathbf{u}_f(n)e(n)] \end{aligned}$$

where $\mathbf{u}_f(n)$ is given by

$$\mathbf{u}_f(n) = \begin{bmatrix} \sum_{i=0}^{I-1} f_i u(n-i) \\ \sum_{i=0}^{I-1} f_i u(n-i-1) \\ \vdots \\ \sum_{i=0}^{I-1} f_i u(n-i-M+1) \end{bmatrix}$$

To simplify the derivation, without loss of the generality, only the gradient of one weight w_p in the weight vector $\mathbf{w}$ will be calculated,

$$\nabla J_{fp} = -2E \left[\sum_{i=0}^{I-1} f_i u(n-i-p) e(n) \right] \quad (6.4)$$

Then substitute (6.2) into above

$$\begin{aligned} \nabla J_{fp} &= -2E \left[\sum_{i=0}^{I-1} f_i u(n-i-p) [d(n) - \sum_{i=0}^{I-1} f_i \sum_{m=0}^{M-1} w_m(n-i) u(n-i-m)] \right] \\ &= -2 \sum_{i=0}^{I-1} f_i E[u(n-i-p) d(n) \\ &\quad - \sum_{i=0}^{I-1} f_i \sum_{m=0}^{M-1} w_m(n-i) u(n-i-p) u(n-i-m)] \end{aligned}$$

$$\begin{aligned}
&= -2 \sum_{i=0}^{I-1} f_i \left[E[u(n-i-p)d(n)] - \sum_{i=0}^{I-1} f_i \sum_{m=0}^{M-1} w_m E[u(n-i-p)u(n-i-m)] \right] \\
&= -2\mathbf{f}^T(\mathbf{t} - \mathbf{f}\mathbf{w})
\end{aligned} \tag{6.5}$$

where

$\mathbf{t} = E[\mathbf{u}(n)d(n)]$ is the cross-correlation vector between the input vector $\mathbf{u}$ and the desired response d .

$\mathbf{r} = E[\mathbf{u}^T(n-i-p)\mathbf{U}(n-i-m)]$ is the auto-correlation vector between the input vector $\mathbf{u}^{I \times 1}$ and the input matrix $\mathbf{U}^{I \times M}$.

Then we use instantaneous estimates for $\mathbf{r}$ and $\mathbf{t}$ that are based on sample values of the input vector and desired response, as defined below,

$$\hat{\mathbf{r}}(n) = \mathbf{u}^T(n)\mathbf{U}(n)$$

and

$$\hat{\mathbf{t}}(n) = \mathbf{u}(n)d(n)$$

The corresponding instantaneous estimate of the gradient is

$$\hat{\nabla} J_{fp}(n) = -2\mathbf{f}^T [\mathbf{u}(n)d(n) - \mathbf{f}\mathbf{u}^T(n)\mathbf{U}(n)\mathbf{w}(n)] \tag{6.6}$$

Substituting the estimate of (6.6) for the gradient vector ∇J in the steepest-

descent algorithm described in (5.9), we get a new recursive relation for updating the weight:

$$\begin{aligned} w_p(n+1) &= w_p(n) - \mu \{ -2\mathbf{f}^T [\mathbf{u}(n)d(n) - \mathbf{f}\mathbf{u}^T(n)\mathbf{U}(n)\mathbf{w}(n)] \} \\ &= w_p(n) + 2\mu\mathbf{f}^T\mathbf{u}(n)[d(n) - \mathbf{f}^T\mathbf{U}(n)\mathbf{w}(n)] \end{aligned} \quad (6.7)$$

Then the whole adaptive algorithm can be described with three equations below:

1. Adaptive filter:

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \quad (6.8)$$

2. Estimation error:

$$e(n) = d(n) - \mathbf{f}^T\mathbf{U}(n)\mathbf{w}(n) \quad (6.9)$$

3. Weight adaptation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu\mathbf{U}^T(n)\mathbf{f}e(n) \quad (6.10)$$

6.3 Normalized LMS

To make LMS algorithm be more robust with respect to power variations of the input vector and to increase the convergence speed of the LMS algorithm without using estimates of the input signal correlation matrix, the normalized LMS algorithm with a variable convergence factor is a natural solution [122],[128]. The normalized LMS algorithm usually converges faster than the LMS algorithm, since it utilizes a variable convergence factor aiming at the minimization of the

instantaneous output error. The updating equation of the LMS algorithm can employ a variable convergence factor $\mu(n)$ in order to improve the convergence rate. In this case, the updating formula is expressed as:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu(n)\mathbf{u}(n)e(n) = \mathbf{w}(n) + \Delta\tilde{\mathbf{w}}(n) \quad (6.11)$$

where $\mu(n)$ must be chosen with the objective of achieving a faster convergence. A possible strategy is to reduce the instantaneous squared error as much as possible. The motivation behind this strategy is that the instantaneous squared error is a good and simple estimate of the MSE.

The instantaneous squared error is given by

$$e^2(n) = d^2(n) + \mathbf{w}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) - 2d(n)\mathbf{w}^T(n)\mathbf{u}(n) \quad (6.12)$$

If a change given by $\tilde{\mathbf{w}}(n) = \mathbf{w}(n) + \Delta\tilde{\mathbf{w}}(n)$ is performed in the weight vector, the corresponding squared error can be shown as

$$\begin{aligned} \tilde{e}^2(n) &= d^2(n) + \mathbf{w}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) - 2d(n)\mathbf{w}^T(n)\mathbf{u}(n) \\ &\quad + 2\Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) + \Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\Delta\tilde{\mathbf{w}}(n) \\ &\quad - 2d(n)\Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n) \\ &= e^2(n) + 2\Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) + \Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\Delta\tilde{\mathbf{w}}(n) \\ &\quad - 2d(n)\Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n) \end{aligned} \quad (6.13)$$

It then follows that

$$\begin{aligned}\Delta e^2(n) &= \tilde{e}^2(n) - e^2(n) \\ &= -2\Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)e(n) + \Delta\tilde{\mathbf{w}}^T(n)\mathbf{u}(n)\mathbf{u}^T(n)\Delta\tilde{\mathbf{w}}(n)\end{aligned}\tag{6.14}$$

In order to increase the convergence rate, the objective is to make $\Delta e^2(n)$ negative and minimum by appropriately choosing $\mu(n)$.

Substitute $\Delta\tilde{\mathbf{w}}(n) = 2\mu(n)e(n)\mathbf{u}(n)$ into the above equation,

$$\Delta e^2(n) = -4\mu(n)e^2(n)\mathbf{u}^T(n)\mathbf{u}(n) + 4\mu^2(n)e^2(n)[\mathbf{u}^T(n)\mathbf{u}(n)]^2\tag{6.15}$$

Let $\frac{\partial \Delta e^2(n)}{\partial \mu(n)} = 0$, the value of $\mu(n)$ will be

$$\mu(n) = \frac{1}{2\mathbf{u}^T(n)\mathbf{u}(n)}\tag{6.16}$$

Use this variable convergence factor, the updating equation for the LMS algorithm is then given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{e(n)\mathbf{u}(n)}{\mathbf{u}^T(n)\mathbf{u}(n)}\tag{6.17}$$

Usually another fixed factor μ is introduced into the updating formula. Also a parameter γ should be included, in order to avoid large step sizes when the power of the input, $\mathbf{u}^T(n)\mathbf{u}(n)$, becomes small. The coefficient updating equation is then

given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\gamma + \mathbf{u}^T(n)\mathbf{u}(n)} e(n)\mathbf{u}(n) \quad (6.18)$$

The resulting algorithm is called the normalized LMS algorithm.

The range of values of μ to guarantee stability can be derived by firstly considering that $E[\mathbf{u}^T(n)\mathbf{u}(n)] = \text{tr}[R]$ and that

$$E \left[\frac{e(n)\mathbf{u}(n)}{\mathbf{u}^T(n)\mathbf{u}(n)} \right] \approx \frac{E[e(n)\mathbf{u}(n)]}{E[\mathbf{u}^T(n)\mathbf{u}(n)]} \quad (6.19)$$

Next, consider that the average value of the convergence factor actually applied to the LMS direction $2e(n)\mathbf{u}(n)$ is $\frac{\mu}{2\text{tr}[R]}$. And finally, by comparing the updating formula of the standard LMS algorithm with that of the normalized LMS algorithm, the desired upper bound result follows:

$$0 < \frac{\mu}{2\text{tr}[R]} < \frac{1}{\text{tr}[R]} \quad (6.20)$$

that is

$$0 < \mu < 2 \quad (6.21)$$

6.4 Leaky LMS

In the implementation, multiplication and addition are involved in the calculation of the filter coefficients. Due to the limited range and precision, the multiplication and addition operations can lead to quantization errors during the process of

truncation and saturation. Over time, these quantization errors might accumulate until an overflow in the filter coefficients occurs. The leaky LMS can help mitigate the problem [121],[122].

The cost function of the leaky LMS algorithm is defined by the following equation:

$$J_{MSE} = E[e(n)^2 + \alpha \sum_{m=0}^M w_m^2 u(n-m)] \quad (6.22)$$

where α is the leaky factor with a range of $(0, 1)$. Because of the presence of α , the cost function of the leaky LMS algorithm is different from that of the standard LMS algorithm. The leaky LMS algorithm mitigates the coefficients overflow problem, as the cost function of this algorithm accounts for both $e^2(n)$ and the filter coefficients.

The corresponding gradient vector will be

$$\nabla J(n) = -2\mathbf{u}(n)d(n) + 2\mathbf{u}(n)\mathbf{u}^T(n)\mathbf{w}(n) + 2\alpha\mathbf{w}(n) \quad (6.23)$$

Then the leaky LMS algorithm updates the coefficients of an adaptive filter by using the following equation:

$$\mathbf{w}(n+1) = (1 - 2\mu\alpha)\mathbf{w}(n) + 2\mu\mathbf{u}(n)e(n) \quad (6.24)$$

α should satisfy the condition below

$$0 \leq \alpha < \frac{1}{2\mu} \quad (6.25)$$

If $\alpha = 0$, the leaky LMS algorithm becomes the same as the standard LMS algorithm.

6.5 Leaky Normalized Filtered-X LMS in HDDs

The leaky, normalized Filtered-X LMS algorithm is used to attenuate the linear/rotational vibration in HDDs. The block diagram of the HDD servo system with leaky, normalized Filtered-X LMS is demonstrated in Fig. 6.2. A FIR filter is chosen as the adaptive filter. The error signal is PES, the filter input is the accelerometer output and the Filtered-X filter is the fitted HDD plant transfer function.

Figure 6.2: Block Diagram for HDD Servo System with Leaky Normalized Filtered-X LMS

The whole adaptation law will be:

1. Adaptive filter:

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \quad (6.26)$$

2. Estimation error:

$$e(n) = d(n) - \mathbf{f}^T \mathbf{U}(n) \mathbf{w}(n) = PES(n) \quad (6.27)$$

3. Weight adaptation:

$$\mathbf{w}(n+1) = (1 - 2\mu\alpha)\mathbf{w}(n) + 2\frac{\mu}{\gamma + \mathbf{u}^T(n)\mathbf{u}(n)}\mathbf{U}^T(n)\mathbf{f}PES(n) \quad (6.28)$$

where

y : the filter output for feedforward into HDD control loop

$\mathbf{w}$: the weight vector

$\mathbf{u}$: the accelerometer output vector

$\mathbf{U}$: the accelerometer output matrix

$\mathbf{f}$: the Filtered-X coefficient vector

μ, α, γ : the constants

6.6 Simulation

To better simulate the practical condition, all data used in simulation are obtained from a real 2.5-inch HDD with 7200rpm, 310k TPI and 29.9 kHz sampling

frequency. PES and the accelerometer output are collected when the HDD is put into the single-tone (1000Hz) vibration environment. PES collected is used to generate the input disturbance.

6.6.1 Vibration Disturbance Generation

The relationship between the input disturbance and PES can be described below

$$PES = \frac{P}{1 + PC}D$$

Therefore

$$D = \frac{1 + PC}{P}PES \quad (6.29)$$

The procedure to get the input disturbance is as follows:

1. Measure the frequency response of $\hat{P}(F) = \frac{P}{1 + PC}$;
2. Get the PES in frequency domain $PES(F) = \text{fft}(PES)$;
3. Calculate the inner product of $PES(F)$ and $1/\hat{P}(F)$;
4. The frequency response of the input disturbance can be obtained: $D(F) = \frac{PES(F)}{\hat{P}(F)}$;
5. The input disturbance in time domain will be: $D(t) = \text{ifft}(D(F))$.

Fig. 6.3 presents PES under pure tone vibration when the HDD is installed into a laptop computer. It can be seen that the pure tone frequency is 1000Hz and PES oscillates with the amplitude of more than 20% track pitch. Fig. 6.4 presents the

corresponding input disturbance, which is calculated by (6.29). The dominant frequency of the input disturbance is 1000Hz.

Figure 6.3: PES in a Single-tone Vibration

6.6.2 Filtered-X Filter

Because the main objective of applying accelerometer-based feedforward algorithm is to handle the linear vibration or rotational vibration, which only contains low frequency signal in the spectrum, a low pass filter is inserted between the accelerometer output and the Filtered-X filter to remove the noise in the accelerometer output. This 'frequency-weighted' filter can be represented by the second order IIR filter below:

$$\frac{u_L(z)}{u(z)} = \frac{d_0 + d_1 z^{-1} + d_2 z^{-2}}{1 + c_1 z^{-1} + c_2 z^{-2}} \quad (6.30)$$

Figure 6.4: Single-tone Input Disturbance

where u is the accelerometer output and u_L is the output of the low pass filter.

Recall the Filtered-X filter,

$$\hat{P} = \frac{P}{1 + PC}$$

$\hat{P}$ is actually the closed-loop VCM response, which can be measured.

In the implementation, a 4th order IIR filter is used to fit $\hat{P}$ as follows:

$$\frac{y_f(z)}{u_L(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3} + b_4 z^{-4}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4}} \quad (6.31)$$

where y_f is the output of the Filtered-X filter.

The match of the phases of the real VCM response and the fitting filter is critical to ensure the stability. The measured frequency response of $\hat{P}$ and the frequency response of the fitting filter (6.31) are both presented in Fig. 6.5. Although there are some mismatches in magnitude responses above 1000Hz, the fitting of phase

response in low frequency range, where we are interested to handle the vibration, is satisfactory. Hence this 4th order filter can help stabilize the system. Because

Figure 6.5: Filtered-X Filter for the HDD

the CPU speed of the microprocessor used in the HDD is increasing rapidly (the CPU speed of the microprocessor in the experiment is up to 320MHz), the implementation of a 4th order IIR filter will not produce too much computational burden to HDD. To save the memories, direct form II is adopted to implement the IIR filter.

6.6.3 Block Diagram in Simulink

To simulate the sampled HDD servo system, a real time model is needed. Simulink is selected to perform this task.

The overall block diagram in Simulink is demonstrated in Fig. 6.6. The system has two inputs: 1. the accelerometer output, which is collected in the real single-tone vibration environment; 2. the input disturbance generated by (6.29). Take note that the accelerometer output and PES must be collected simultaneously in vibration environment. The sampling frequency is set at 29.9kHz and the order of the adaptive filter is set at 6.

All functional blocks in the figure are described below:

LowPassFilter. A low pass filter to remove high frequency noise in the accelerometer output. The transfer function is the same as (6.30).

FilteredXFilter. The transfer function is the same as (6.31).

Sfun_LMS. The LMS algorithm is included in this block Three operations are performed in this s-function:

- define basic S-Function block characteristics, including the sampling period, initial conditions of discrete states, and the sizes of arrays.
- run the Leaky Normalized LMS: perform normalization, calculate coefficients, update all discrete states, and compute the filter output.
- output all s-function states.

Controller. The main loop state feedback controller in the form of transfer function.

NotchFilters. A few notch filters are connected in series to handle the mechanical modes in VCM plant.

VCMPlant. The real VCM plant is measured including all mechanical modes.

ZOH. A Zero-Order-Holder with the sampling frequency at 29.9 kHz.

6.6.4 Simulation Results

Fig. 6.7 presents PES improvement by the Leaky Normalized Filtered-X LMS algorithm. The upper plot presents PES in time domain and the lower plot shows the PES spectrum in frequency domain. Without the proposed algorithm, PES oscillates at 1000Hz with the amplitude of more than 20% track pitch; with the algorithm, the amplitude of PES at 1000Hz is reduced a lot. The convergence of PES after the algorithm is switched on is shown in Fig. 6.8. It can be seen that PES is suppressed to a lower level within 100 servo samples.

The simulation results proof the effectiveness of the proposed design. Then the implementation and experimentation are performed.

6.7 Implementation and Experimentation

6.7.1 Implementation of Normalized Filtered-X LMS

To minimize the computation load, the order of the adaptive FIR filter (6.26) should be the minimum value that can achieve satisfactory performance. In implementation, the order of the filter is determined by trial-and-error method and a 6th order FIR filter is used.

$$\begin{aligned} y(n) = & w_0(n)u_L(n) + w_1(n)u_L(n-1) + w_2(n)u_L(n-2) + w_3(n)u_L(n-3) \\ & + w_4(n)u_L(n-4) + w_5(n)u_L(n-5) \end{aligned} \quad (6.32)$$

where $w_1(n), w_2(n), w_3(n), w_4(n), w_5(n)$ and $w_6(n)$ are weights to be updated by (6.28).

μ, α, γ in (6.28) are set at 0.5, 0.9998 and 1 respectively.

6.7.2 Intermittent Algorithm for Linear Vibration and Rotational Vibration

Because the effects of linear vibration and rotational vibration on PES are different, the transfer functions from the accelerometer output to PES are not same and two separate LMS algorithms are needed to handle those two kinds of vibrations.

Let us recall Section 5.3 that the linear acceleration and rotational acceleration

can be obtained via two equations below

$$A_L = \frac{LA_1 + LA_2}{2}$$

$$A_R = \frac{LA_1 - LA_2}{2}$$

To deal with linear vibration, u in (6.30) should be A_L ; to deal with rotational vibration, u should be R_L .

If both the two algorithms are running at every sample, heavy computational load will be put to the microprocessor and the bandwidth for read/write firmware will be reduced much. Consequently, the read/write performance in vibration environment will be degraded greatly.

The major frequency components for both the linear vibration and rotational vibration are below 1kHz; normally the sampling frequency of the HDD is much higher than 1kHz, so that we have an opportunity to run each LMS algorithm in a lower rate. For the HDD we used in experiment, the sampling frequency is nearly 30kHz. According to the sampling theorem, the sampling frequency needs to be two times higher than the highest frequency of the vibration, which is 1kHz. Therefore, intermittent LMS at a half-sampling rate for both the linear vibration and rotational vibration is adopted, that is, in sample n , the LMS algorithm for linear vibration is performed; in sample $n + 1$, the LMS algorithm for rotational vibration is executed.

6.7.3 Experimental Results

Experimental Setup

A commercially available 2.5-inch Seagate HDD was used in the experimentation. The rotational speed is 7200rpm, the track density is 310k TPI and the sampling frequency is 29.9 kHz. The code with the algorithm was downloaded to the drive.

Three experiments were carried out to test the new algorithm.

1. **Pure tone test.** The drive was placed into a laptop computer, which was playing the pure tone sound during testing;
2. **Linear vibration test.** The drive was installed on a linear shaker for testing;
3. **Rotational vibration test.** The drive was installed on a rotational shaker for testing.

Pure tone Test

Pure tone is a tone with a sinusoidal waveshape. Measuring the response of the algorithm to pure tone disturbance is a good way to test the stability and the convergence of the algorithm. The HDD was placed into a laptop, as shown in Fig. 4.20. A pure tone wave with the frequency set at 500Hz was played by the laptop. The speaker was put to full volume.

Fig. 6.9 compares PES with and without the Leaky Normalized Filtered-X LMS under pure tone disturbance. The upper plot presents PES in time domain and

the lower plot shows the PES spectrum in frequency domain. The main loop controller does not have enough attenuation on the pure tone disturbance, and PES oscillates with large amplitude at 500Hz; while Filtered-X LMS can suppress pure tone-induced PES effectively. Fig. 6.10 presents in detail how PES converges with the proposed algorithm when single-tone vibration comes.

Fig. 6.11 demonstrates the convergence of all weights in FIR filter (6.26). After the pure tone vibration comes, all six weights adapt and then stabilize within 400 servo samples.

Linear Vibration Test

To perform a standard linear vibration test, the HDD was mounted vertically onto a linear shaker, as shown in Fig. 4.18. A signal with flat amplitude, random frequencies at 0-500Hz was used to drive the shaker.

Fig. 6.12 presents the PES improvement by the algorithm when the vibration amplitude is equal to 1.5Grms. It can be seen that Leaky Normalized Filtered-X LMS algorithm suppresses the disturbances in 0-500Hz successfully and achieves 29% reduction in PES 1σ value. To check whether the algorithm can perform well in vibrations with high amplitude, a 4Grms linear vibration is applied. The algorithm is even more efficient when the vibration amplitude is higher. As shown in Fig. 6.13, PES 1σ is improved by 39% when the vibration amplitude is equal to 4Grms.

Rotational Vibration Test

The disk drive was installed on a rotational shaker, as shown in Fig. 6.14. The shaker is rotating with the random frequencies of 0-500Hz and the flat amplitude of 8rads.

Fig. 6.15 shows PES response in both the time domain and frequency domain. PES is improved by 34% in terms of 1σ .

6.8 Summary

In this chapter, the Filtered-X LMS algorithm is derived; the normalized LMS algorithm is utilized to make LMS algorithm be more robust with respect to power variations of the accelerometer output and to increase the convergence speed of the LMS algorithm; and the leaky LMS is used to mitigate the problem of accumulated quantization error in the HDD implementation. Pure tone, linear vibration and rotational vibration tests were carried out. The experimental results verify the effectiveness of the algorithm.

This algorithm is very suitable for the applications wherein the consumer devices encounter the vibrations with large amplitude or single shock event. The algorithm cannot perform well under vibrations in middle or high frequency, such as the pink noise or music, because the convergence of the LMS method is not fast enough to track such vibrations. So the algorithm in this chapter and the method in Chapter 4 complement each other to provide a total solution to all kinds of vibrations.

Compared to LMS, the other adaptive filtering algorithm, RLS, normally has faster convergence and smaller tracking error. In the next chapter, a Weighted QRD-based Filtered-X RLS will be studied to reject the vibrations.

Figure 6.6: LMS Block Diagram in Simulink

Figure 6.7: PES for Single-tone Simulation with LMS

Figure 6.8: PES Convergence for Single-tone Simulation with LMS

Figure 6.9: PES Improvement by LMS in Single-tone Vibration

Figure 6.10: PES Convergence in Single-tone Vibration

Figure 6.11: LMS Weights Adaptation in Single-tone Vibration

Figure 6.12: PES Improvement by LMS in 1.5G Linear Vibration

Figure 6.13: PES Improvement by LMS in 4G Linear Vibration

Figure 6.14: The Shaker for Rotational Vibration

Figure 6.15: PES Improvement by LMS in Rotational Vibration

Chapter 7

Vibration Rejection by Weighted QRD-based Filtered-X RLS in HDDs

Normally the standard RLS algorithm cannot be directly used for practical applications because of some stability issues, which are, however, not as critical as in LMS-based algorithms [129],[130]. The QR-Decomposition-based RLS can solve the problem of numerical stability in implementation [121]. The Filtered-X algorithm will help maintain the stability of RLS algorithm in active control applications. The weighted RLS is suitable for time-varying environment [121].

This chapter is organized as follows: Section 7.1 gives an introduction to the exponentially weighted Least Square Estimation. Section 7.2 presents QR-Decomposition-based RLS . Section 7.3 summarizes the weighted QRD-based Filtered-X RLS al-

gorithm in HDDs. Simulation method and simulation results are given in Section 7.4.

7.1 Exponentially weighted Least Square Estimation

In time-varying environment, the exponentially weighted RLS is widely used. The least squares criterion in (5.18) is modified to

$$J_{LS}(m) = \sum_{k=1}^m \lambda^{m-k} e(k)^2 \quad (7.1)$$

where $0 < \lambda < 1$ is the weighting factor or forgetting factor. The latest data is given larger weights than old data.

As in Section 5.4.3, the coefficient vector can be obtained by setting the gradient equal to zero,

$$\mathbf{w}_{LS} = \mathbf{X}_{uu}^{-1} \mathbf{x}_{du} \quad (7.2)$$

and

$$\mathbf{X}_{uu}(m) = \lambda \mathbf{X}_{uu}(m-1) + \mathbf{u}(m) \mathbf{u}^T(m) \quad (7.3)$$

$$\mathbf{x}_{du}(m) = \lambda \mathbf{x}_{du}(m-1) + \mathbf{u}(m) d(m) \quad (7.4)$$

The recursive form of $\mathbf{w}_{LS}$ is

$$\mathbf{w}_{LS}(m) = \mathbf{w}_{LS}(m-1) + \mathbf{X}_{uu}(m)^{-1} \mathbf{u}(m) [d(m) - \mathbf{u}^T(m) \mathbf{w}_{LS}(m-1)] \quad (7.5)$$

To apply the matrix inversion lemma on $\mathbf{X}_{uu}(m)^{-1}$, we define $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ in (5.24) as

$$\mathbf{A} = \lambda \mathbf{X}_{uu}(m)$$

$$\mathbf{B} = \mathbf{u}(m)$$

$$\mathbf{C} = \mathbf{I}$$

$$\mathbf{D} = \mathbf{u}^T(m)$$

Then we get

$$\mathbf{X}_{uu}^{-1}(m) = \frac{1}{\lambda} \left[\mathbf{X}_{uu}^{-1}(m-1) - \frac{\mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m)\mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1)}{\lambda + \mathbf{u}^T(m)\mathbf{X}_{uu}^{-1}(m-1)\mathbf{u}(m)} \right] \quad (7.6)$$

Define

$$\mathbf{P}(m) = \mathbf{X}_{uu}^{-1}(m)$$

We can get

$$\mathbf{P}(m) = \frac{1}{\lambda} \left[\mathbf{P}(m-1) - \frac{\mathbf{P}(m-1)\mathbf{u}(m)\mathbf{u}^T(m)\mathbf{P}(m-1)}{\lambda + \mathbf{u}^T(m)\mathbf{P}(m-1)\mathbf{u}(m)} \right] \quad (7.7)$$

and

$$\mathbf{w}(m+1) = \mathbf{w}(m) + \mathbf{P}(m)\mathbf{u}(m)e(m)$$

7.2 QR-Decomposition-based RLS

For a digital implementation of the adaptive filter, the numerical stability must be considered, or RLS algorithm will suffer from numerical instability due to finite precision computations [121],[131],[132].

In practice, the input data and internal calculations are all quantized to a finite precision that is determined by design and cost considerations. Consequently, the quantization process has the effect of causing the performance of a digital implementation of the algorithm to deviate from its theoretical value. There are two main sources of quantization error:

1. Analog-To-Digital conversion. Given that the input data, the accelerometer output, is in analog form, an Analog-To-Digital Converter (ADC) must be used to obtain the numerical representation of the accelerometer output, therefore a quantization process is unavoidable.
2. Finite-word-length arithmetic. In a microprocessor, a finite word length is commonly used to store the result of internal arithmetic calculations. Assuming that no overflow takes place during the course of computation, additions do not introduce any error, whereas each multiplication introduces an error after the product is quantized.

When the tap weights of the adaptive filter are updated on a continuous base, the filter has propagation on the quantization errors, causing its performance to deviate from the ideal form of the filter. Indeed, it is possible for the deviation to be of a catastrophic nature, in the sense that the errors resulting from the use of the finite-precision arithmetic may accumulate without bound. Ultimately, the filter is driven into an overflow condition, and the algorithm is said to be numerically unstable.

Basically, the standard RLS algorithm has the problem of the numerical instability. Forming the inner product $\mathbf{u}(m)\mathbf{u}^T(m)$ in equation (7.7) is known to be

extremely damaging from a numerical point of view. The squaring doubles the dynamic range, and hence the wordlength has to be doubled, or else accuracy is halved (roughly speaking). A better algorithm is based on the QR decomposition.

QRD-based Least Square Estimation

Recalling the cost function (7.1)

$$J_{LS}(m) = \sum_{k=1}^m \lambda^{m-k} e(k)^2 = \sum_{k=1}^m \lambda^{m-k} [d(k) - \mathbf{u}^T(k) \mathbf{w}(k)]^2$$

The RLS algorithm recursively updates the coefficient vector $\mathbf{w}$ to minimize this cost function. The same problem can be rewritten as a function of increasing dimension matrices and vectors which contain all the weighted signal information available so far for the adaptive filter. These matrices are defined as follows:

$$\begin{aligned} \mathbf{U}^T(k) &= \begin{bmatrix} u(k) & \lambda^{\frac{1}{2}}u(k-1) & \cdots & \lambda^{\frac{k-1}{2}}u(1) & \lambda^{\frac{k}{2}}u(0) \\ u(k-1) & \lambda^{\frac{1}{2}}u(k-2) & \cdots & \lambda^{\frac{k-1}{2}}u(0) & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ u(k-N) & \lambda^{\frac{1}{2}}u(k-N-1) & \cdots & 0 & 0 \end{bmatrix} \\ &= [\mathbf{u}(k) \quad \lambda^{\frac{1}{2}}\mathbf{u}(k-1) \quad \vdots \quad \lambda^{\frac{k-1}{2}}\mathbf{u}(1) \quad \lambda^{\frac{k}{2}}\mathbf{u}(0)] \end{aligned} \quad (7.8)$$

$$\mathbf{y}(k) = \mathbf{U}(k) \mathbf{w}(k) = \begin{bmatrix} y(k) \\ \lambda^{\frac{1}{2}}y(k-1) \\ \vdots \\ \lambda^{\frac{k}{2}}y(0) \end{bmatrix} \quad (7.9)$$

$$\mathbf{d}(k) = \begin{bmatrix} d(k) \\ \lambda^{\frac{1}{2}} d(k-1) \\ \vdots \\ \lambda^{\frac{k}{2}} d(0) \end{bmatrix} \quad (7.10)$$

$$\mathbf{e}(k) = \begin{bmatrix} e(k) \\ \lambda^{\frac{1}{2}} e(k-1) \\ \vdots \\ \lambda^{\frac{k}{2}} e(0) \end{bmatrix} = \mathbf{d}(k) - \mathbf{y}(k) \quad (7.11)$$

Then the cost function can be rewritten as

$$J_{LS}(m) = \mathbf{e}^T \mathbf{e} \quad (7.12)$$

The optimal solution to the least-squares problem at a given instant of time k can be found by solving the following equation

$$\mathbf{U}^T(k) \mathbf{U}(k) \mathbf{w}(k) = \mathbf{U}^T(k) \mathbf{d}(k) \quad (7.13)$$

But solving this equation can be a problem from a numerical point of view, and the QR decomposition-based approach will be a better solution.

The QR decomposition (QRD) of the matrix U is given by

$$\underbrace{\mathbf{U}}_{L \times N} = \underbrace{\mathbf{Q}}_{L \times N} \underbrace{\mathbf{R}}_{N \times N} \quad (7.14)$$

where $\mathbf{Q}$ is orthogonal, i.e.

$$\mathbf{Q}^T \mathbf{Q} = \mathbf{I} \quad (7.15)$$

and $\mathbf{R}$ is an upper triangular matrix (with positive diagonal elements). Every matrix $\mathbf{U}$ can be decomposed in this fashion. A feature of the QRD factorization that is particularly important in view of practical applications/computations is as follows,

$$\mathbf{U}^T \mathbf{U} = \mathbf{R}^T \mathbf{R} \quad (7.16)$$

The matrix $\mathbf{R}$ is then referred to as the Cholesky factor of the normal matrix $\mathbf{U}^T \mathbf{U}$, sometimes also referred to as the square-root of $\mathbf{U}^T \mathbf{U}$.

The solution of (7.13) can be transformed into:

$$\begin{aligned} \mathbf{w}_{LS} &= [\mathbf{R}^T \mathbf{Q}^T \mathbf{Q} \mathbf{R}]^{-1} \mathbf{R}^T \mathbf{Q}^T \mathbf{d} \\ &= [\mathbf{R}^T \mathbf{R}]^{-1} \mathbf{R}^T \mathbf{z} \\ &= \mathbf{R}^{-1} \mathbf{z} \end{aligned} \quad (7.17)$$

where $\mathbf{z} = \mathbf{Q}^T \mathbf{d}$

The QRD is seen to provide a numerically sound alternative to computing the LS solution, wherein forming the normal matrix $\mathbf{U}^T \mathbf{U}$ is avoided. Once the QRD is available, the $\mathbf{w}_{LS}$ is readily obtained as the solution to a triangular set of equations,

$$\mathbf{R} \mathbf{w}_{LS} = \mathbf{z} \quad (7.18)$$

i.e. through a back substitution.

QRD-based RLS

The QRD can be computed in several ways. The *Givens Rotation* method is attractive for RLS because the entries in the input matrix are zeroed in particular manner to obtain the triangular form [121].

The *Givens Rotation* is a rank-two modification of the $m \times m$ identity of the form

$$\mathbf{G}_{i,j,\theta} = \begin{bmatrix} \mathbf{I}_{i-1} & 0 & 0 & 0 & 0 \\ 0 & \cos \theta & 0 & \sin \theta & 0 \\ 0 & 0 & \mathbf{I}_{j-i-1} & 0 & 0 \\ 0 & -\sin \theta & 0 & \cos \theta & 0 \\ 0 & 0 & 0 & 0 & \mathbf{I}_{m-j} \end{bmatrix} \quad (7.19)$$

where $\mathbf{I}_n$ is an $n \times n$ identity matrix. Premultiplication of an m -vector $\mathbf{x}$ by $\mathbf{G}_{i,j,\theta}$ amounts to a rotation of θ degrees in the i, j coordinate plane:

$$\tilde{\mathbf{x}} = \mathbf{G}_{i,j,\theta} \mathbf{x}$$

with $\tilde{\mathbf{x}}$ components as follows

$$\begin{aligned} \tilde{x}_i &= \cos \theta x_i + \sin \theta x_j \\ \tilde{x}_j &= -\sin \theta x_i + \cos \theta x_j \\ \tilde{x}_l &= x_l \quad \text{for } l \neq i, j \end{aligned}$$

The formulas above clearly show that we can force x_j to be zero by setting

$$\tan \theta = \frac{x_j}{x_i} \quad (7.20)$$

Thus, a Givens rotation can be used to zero a specific entry in a vector.

By applying successive Givens rotations, all entries of matrix $\mathbf{U}$ below the main diagonal are zeroed and the required triangular matrix is produced.

$$\begin{bmatrix} \mathbf{R} \\ 0 \end{bmatrix} \leftarrow \mathbf{G}_{i_k, j_k, \theta_k} \cdots \mathbf{G}_{i_2, j_2, \theta_2} \mathbf{G}_{i_1, j_1, \theta_1} \mathbf{U} \quad (7.21)$$

where k is the number of elements below the main diagonal.

For recursively updating from time k to $k+1$, a QRD-updating is needed. Assume we have computed the QRD of the matrix U at time k , i.e.

$$\mathbf{U}(k) = \mathbf{Q}(k) \begin{bmatrix} \mathbf{R}(k) \\ 0 \end{bmatrix} \quad (7.22)$$

Our aim is then to compute the QRD at time $k+1$. Instead of computing the QRD at time $k+1$ from scratch, it is much more efficient to start from the known QRD at time k and to update it accordingly.

$$\begin{bmatrix} \mathbf{R}(k) \\ \mathbf{u}^T(k+1) \end{bmatrix} = \mathbf{Q}(k+1) \begin{bmatrix} \mathbf{R}(k+1) \\ 0 \end{bmatrix} \quad (7.23)$$

The left-hand side matrix is a 'triangular-plus-one-row' matrix. Computing the QRD of such a matrix is often referred to as 'QRD-updating'.

The $w_{LS}(k+1)$ then can be obtained from the back substitution

$$\mathbf{R}(k+1)\mathbf{w}_{LS}(k+1) = \mathbf{z}(k+1) \quad (7.24)$$

7.3 Weighted QRD-based Filtered-X RLS

For active control applications, the estimation error that RLS needs to minimize in least-square sense will be

$$e(k) = d(k) - \mathbf{f}^T \mathbf{U}(k) \mathbf{w}(k)$$

Let

$$\mathbf{u}_f^T = \mathbf{f}^T \mathbf{U}(k), \quad (7.25)$$

Therefore, to minimize the error

$$e(k) = d(k) - \mathbf{u}_f^T \mathbf{w}(k)$$

becomes a standard RLS problem. Because the RLS algorithm is derived from a deterministic formulation, through the substitution in (7.25), Filtered-X RLS weight adaptation can be easily obtained.

The whole adaptive algorithm for QRD-based Filtered-X RLS can be described by three laws below:

1. Adaptive filter:

$$y(k) = \mathbf{w}^T(k) \mathbf{u}(k) \quad (7.26)$$

2. Estimation error:

$$e(k) = d(k) - \mathbf{f}^T \mathbf{U}(k) \mathbf{w}(k) = PES(k) \quad (7.27)$$

3. Weight adaptation:

During the initialization period, i.e., from $k = 0$ to $k = N$, the weights can be obtained through solving equation (7.13) without using any matrix inversion.

For $k = 0$ and $u(0) \neq 0$

$$w_0(0) = \frac{d(0)}{u_f(0)}$$

For $k = 1$

$$w_0(1) = \frac{d(0)}{u_f(0)}$$

$$w_1(1) = \frac{-u_f(1)w_0(1) + d(1)}{u_f(0)}$$

For $k = 2$

$$w_0(2) = \frac{d(0)}{u_f(0)}$$

$$w_1(2) = \frac{-u_f(1)w_0(2) + d(1)}{u_f(0)}$$

$$w_2(2) = \frac{-u_f(2)w_0(2) - u_f(1)w_1(2) + d(2)}{u_f(0)}$$

At the instant k , we can show by induction that

$$w_i(k) = \frac{-\sum_{j=1}^i u_f(j)w_{i-j}(k) + d(i)}{u_f(0)} \quad (7.28)$$

The equation above represents the so-called back-substitution algorithm.

At the instant $k + 1$, 'QRD-updating' is performed to get QRD of both $\mathbf{U}$ and $\mathbf{d}$

$$\begin{bmatrix} \frac{\mathbf{U}_f(k)}{\mathbf{u}_f^T(k+1)} \end{bmatrix} = \begin{bmatrix} \frac{\mathbf{R}(k)}{\mathbf{u}_f^T(k+1)} \end{bmatrix} = \mathbf{Q}(k+1) \begin{bmatrix} \frac{\mathbf{R}(k+1)}{0} \end{bmatrix} \quad (7.29)$$

$$\mathbf{z}(k+1) = \mathbf{Q}^T(k+1)\mathbf{d}(k+1)$$

The $\mathbf{w}_{LS}(k+1)$ then can be obtained from the back substitution

$$\mathbf{R}(k+1)\mathbf{w}_{LS}(k+1) = \mathbf{z}(k+1) \quad (7.30)$$

7.4 Simulation

To better simulate the practical condition, all data used in simulation are obtained from a real 2.5-inch HDD with 7200rpm, 310k TPI and 29.9 kHz sampling frequency. PES and the accelerometer output are collected when the HDD is put into the single-tone (1000Hz) vibration environment. PES collected is used to generate the input disturbance. The details of vibration disturbance generation can be found in Section 6.6.1.

7.4.1 Block Diagram in Simulink

To simulate the sampled HDD servo system, a real time model is needed. Simulink is selected to perform this task.

The overall block diagram in Simulink is demonstrated in Fig. 7.1. The inputs

of the system are same with those described in Section 6.6.3. The order of the adaptive filter is set at 6.

All functional blocks in the figure are described below:

LowPassFilter. A low pass filter to remove high frequency noise in the accelerometer output. The transfer function is the same as (6.30).

FilteredXFilter. The transfer function is the same as (6.31).

Sfun_RLS. The RLS algorithm is included in this block. Three operations are performed in this s-function:

- define basic S-Function block characteristics, including the sampling period, initial conditions of discrete states, and the sizes of arrays.
- run the QR-Decomposition-based RLS algorithm: perform QR-Decomposition, calculate coefficients, update all discrete states, and compute the filter output.
- output all s-function states.

Controller. The main loop state feedback controller in the form of transfer function.

NotchFilters. A few notch filters are connected in series to handle the mechanical modes in VCM plant.

VCMPlant. The real VCM plant is measured including all mechanical modes.

ZOH. A Zero-Order-Holder with the sampling frequency at 29.9 kHz.

7.4.2 Simulation Results Analysis

1. PES

PES improvement by the weighted QRD-based Filtered-X RLS can be seen in Fig. 7.2. The upper plot presents PES in time domain and the lower plot shows the PES spectrum in frequency domain. Without the proposed algorithm, PES oscillates at 1000Hz with the amplitude of more than 20% track pitch; with the algorithm, the amplitude of PES is reduced to below 15% track pitch in most of the servo samples. In frequency domain, it can be seen that the large PES at 1000Hz is removed. Fig. 7.3 presents how PES converges in the first few hundred samples after the algorithm is switched on. It can be seen that the algorithm responds fast and suppresses PES within 30 servo samples.

2. The output of the adaptive filter for feedforward

The output of the adaptive filter is feedforwarded into the main control loop to attenuate the disturbance, as shown in Fig. 7.4 in both the time and frequency domains. To effectively suppress the 1000Hz pure tone disturbance, the dominant frequency of the adaptive filter output is 1000Hz.

3. The coefficients of the adaptive filter

Fig. 7.5 demonstrates how the 6 coefficients of the FIR filter adapt to the vibration environment. After the algorithm is switched on, all six weights adapt and then stabilize at around 500 servo samples.

4. Comparison between LMS and RLS

The simulation results of RLS are compared with those of LMS in Chapter 6.

Fig. 7.6 compares PES level of RLS and LMS in steady state. The upper plot presents PES in time domain and the lower plot shows the PES spectrum in frequency domain. It can be seen that RLS algorithm can achieve 16% more PES reduction than LMS algorithm under the same disturbance.

Fig. 7.7 gives the comparison of convergence speed between RLS and LMS. It can be seen that RLS converges faster than LMS.

7.5 Summary

In this chapter, a weighted QRD-based Filtered-X RLS method is used in an HDD to reject the vibrations. QR-Decomposition is employed to solve the problem of numerical stability of RLS. The exponentially weighted RLS puts more weights into the latest data in a time-varying environment. A simulation condition, which is very similar to real HDDs under pure tone vibrations, is created to test the algorithm. Simulation results show that the method is more effective than LMS in suppressing the pure tone vibration and achieving faster convergence and more PES reduction.

Due to the computational complexity, the algorithm in this chapter is difficult to implement in an HDD currently and will possibly find its applications in the near future, which will be discussed more in next chapter.

Figure 7.1: RLS Block Diagram in Simulink

Figure 7.2: PES for Single-tone Simulation with RLS

Figure 7.3: PES Convergence for Single-tone Simulation with RLS

Figure 7.4: The Output of the Adaptive Filter

Figure 7.5: RLS Weights Adaptation for Single-tone Simulation

Figure 7.6: PES Comparison for Single-tone Simulation

Figure 7.7: Convergence Comparison for Single-tone Simulation

Chapter 8

Conclusion and Recommendations

8.1 Conclusion

As the HDD finds more applications in various mobile consumer devices, HDD servo control needs to improve the performance in the seeking acoustics and vibration rejection. This research provides comprehensive solutions to these two problems.

Firstly, the mathematical model of the HDD is given in Chapter 2. The rigid body model of the VCM with a current driver is obtained, and then, for the whole plant used in the design, the resonance mode, the amplifier saturation, disturbances and noises are also taken into consideration. Both the analytic derivation and system identification results are presented in this chapter.

Seeking acoustics improvement is achieved by the algorithm described in Chapter 3. A Two-Degree-Of-Freedom (TDOF) seeking controller for minimizing the seeking acoustics is proposed and the TDOF model reference controller is employed. The sinusoidal wave is used in the proposed design as the reference input. The current saturation and the maximum velocity are taken into account in the trajectory generation so that the single seeking controller can be applied to all seek lengths. Most importantly, an acoustics factor is included in the reference trajectory generation so that the acoustics level can be adjusted via seek design to reach a compromise between the access time and the acoustics level. The algorithm is implemented in a real HDD and compared with PTOS algorithm in various experiments. With the systematic design of seeking controller, the seeking acoustics in HDDs is greatly reduced without the significant increase of the seeking time.

To handle various external vibrations, two kinds of vibration rejection schemes are proposed in this research. An add-on loop gain booster algorithm is used to deal with the pink noise and the linear/rotational vibrations with relatively low amplitude; two adaptive filtering based algorithms are developed to reject the pure tone disturbance and the linear/rotational vibrations with high amplitude.

A novel vibration compensation method is proposed in Chapter 4. It is an add-on scheme and the add-on feature will be turned on only in the specific vibration environment. The scheme comprises two parts: the vibration detection through analysis of the vibration sensor output or PES, and the vibration compensation through the add-on feature. The vibration detection can determine which kind of vibration environment the HDD is in and therefore the corresponding add-on

feature will be compensated. The add-on feature increases the loop gain over a selected frequency band for enhanced disturbance rejection in that frequency band. One major advantage of this method over conventional methods applied in HDD is that the vibration rejection in some frequencies can be improved without the compromise of the performance in the other frequencies. Furthermore, the scheme is not based on an accurate modeling, so it is less sensitive to the variation of the plant parameters. The transient response in switching on/off the add-on feature is successfully shortened by the reset control. RIDE is adopted to form the reset controller. The scheme is implemented in real HDD and produces the satisfactory experimental results under various vibrations.

Chapter 5 gives an introduction to the accelerometer and the accelerometer-based feedforward control. Two linear accelerometers are used to sense both the linear vibration and rotational vibration. Two kinds of the adaptive filtering algorithms are described: LMS and RLS.

A Leaky Normalized Filtered-X LMS algorithm is presented in Chapter 6. The normalized LMS algorithm will make LMS algorithm be more robust with respect to power variations of the input vector and increase the convergence speed of the LMS algorithm. The leaky LMS can help mitigate the problem of accumulated quantization error in implementation. The Filtered-X LMS is derived. The algorithm is implemented in a real HDD and the experimental results show significant PES reduction in pure tone test and linear/rotational vibration tests.

In Chapter 7, the development of the weighted QRD-based Filtered-X RLS in HDD is demonstrated. The weighted RLS is suitable for time-varying environment. The QR-Decomposition-based RLS can solve the problem of numerical

stability in implementation. Simulation is done in Simulink. A real-time model is used and the input data is collected in the real HDD under vibrations. The simulation results demonstrate how the algorithm rejects the disturbance. The algorithm is not implemented in real HDD due to its computational complexity. Compared with the LMS algorithm, RLS algorithm needs much more mathematical operations and memory locations. The computational complexity of the LMS algorithm is $\mathcal{O}(N)$, where N is the filter length, while the complexity of RLS is $\mathcal{O}(N^2)$. When N is large, the difference can be significant. Although LMS has the advantage in the numerical stability and computational complexity, RLS has faster convergence and smaller tracking error, as shown in a comparative study between LMS and RLS in the simulation.

In conclusion, with the algorithms developed in this research, HDDs in mobile consumer devices can have a satisfactory performance:

1. The users can enjoy the audio/video programmes without the disturbance from HDD seeking sound, even when there are frequent read/write operations on HDD;
2. A smooth data transfer between the HDD and the host can be maintained under various vibrations, i.e., when the users are walking, cycling, jogging or playing music loudly with the speaker on.

8.2 Recommendations

Nowadays, power saving is very important for HDDs used in mobile consumer devices, and to save power, most of HDDs have various power management schemes. The most frequently used power saving measure is to shut down the demodulator when no read/write commands come for some time. Then VCM is in open-loop control immediately and just driven by a fixed current to counteract the flexible cable force and friction force. From closed-loop control to open-loop control, the head will be moving for some time. Upon a new read/write command, servo needs to do a seek operation and this seek will have an initial velocity. The seek algorithm in this research assumes that all seek operations are started with zero initial velocity. The control loop will have to produce a large force to handle the big initial velocity. Consequently a large jerk in current will generate big acoustic noise. To tackle this problem, an initial value compensation (IVC) algorithm [133]-[135] needs to be developed to complement the seeking algorithm.

For QR-decomposition based RLS feedforward algorithm, the algorithm consumes a lot of computation time due to its $\mathcal{O}(N^2)$ computational complexity and the calculation of the square root; on the other hand, a HDD servo system is a sampled system with a high sampling frequency and a short sampling period; furthermore, servo control needs to share the short sampling interval with read/write firmware to perform read/write operations, so it is difficult to implement the algorithm in real hard disc drive currently. In future research, some efforts need to be put to reduce the computational complexity of the QR-decomposition based RLS algorithm. The lattice realization of recursive allows modular implemen-

tation and requires a reduced number of arithmetic operations [139],[140]. The lattice-based formulation provides the prediction and the general adaptive filter solutions of all intermediate orders from 1 to N simultaneously. Consequently, the order of the adaptive filter can be increased or decreased without affecting the lower order solutions. This property allows us to activate or deactivate sections of the lattice realization in real time according to different vibration sources or different performance requirements. Some research has provided square-root free solution for QR-decomposition-based RLS [136]-[138]. Implementation of the systolic structures requires less computational complexity [122],[137].

As the CPU speed of the microprocessor used in the HDD is increasing rapidly and dual processors technology, in which one processor is fully used by servo control and the other is used for read/write firmware, is recently adopted by HDD manufacturers, the QR-decomposition based RLS feedforward algorithm with reduced computational complexity can be applied to a real HDD in the near future.

Author's Publications

1. J. Y. Wang, Q. W. Jia and Y. Y. Wang, "Hard disk drive seeking acoustics reduction by a new Two-Degree-of-Freedom seeking controller", *IEEE Transactions on Magnetics*, vol. 46, No. 6, pp. 1587-1590, Jun. 2010.
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