“Am I talking to a human or a robot?”: A preliminary study of human’s perception in human-humanoid interaction and its effects in cognitive and emotional states

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Abstract. The current preliminary study concerns the identification of the effects human-humanoid interaction can have on human emotional states and behaviors, through a physical interaction. Thus, we have used three cases where people face three different types of physical interaction with a neutral person, Nadine social robot and the person on which Nadine was modelled, Professor Nadia Thalmann. To support our research, we have used EEG recordings to capture the physiological signals derived from the brain during each interaction, audio recordings to compare speech features and a questionnaire to provide psychometric data that can complement the above. Our results mainly showed the existence of frontal theta oscillations while interacting with the humanoid that probably shows the higher cognitive effort of the participants, as well as differences in the occipital area of the brain and thus, the visual attention mechanisms. The level of concentration and motivation of participants while interacting with the robot were higher indicating also higher amount of interest. The outcome of this experiment can broaden the field of human-robot interaction, leading to more efficient, meaningful and natural human-robot interaction.

Keywords: Human-Robot interaction, EEG, speech, social robots, social cognition, emotional communication

1 Introduction

The communication between human beings has been guided and facilitated by the existence of emotions. Emotions, as an inherent internal procedure, are the mirror of what we feel, allowing us to perceive and understand our environment, including ourselves. The importance of emotions in human communication has been supported since 1973 by Ekman [1], influenced by Darwin’s work. Fast-forward to the 21st century, the focus has shifted towards the relationship between humans and machines, creating the broad area of affective computing, examining emotions and perception evoked by human-computer interaction or the use of emotions for the emotional intelligence of the machines. The ultimate purpose is the facilitation of the smooth communication between humans and computer-generated characters or robots.

The study and comparison between emotions and neural processing in human-human and human-computer interaction have recently been in the focus of various research studies. Robots, until recently, were considered unable to have inner experiences and independent thought [2]. Towards this direction, research aims to develop robots which will be able to comprehend people [3]. Thus, an interesting question is whether interacting with them could trigger human-like responses. To that end, enriching robots with a degree of emotional intelligence could lead to more efficient, meaningful and natural human-robot interactions.

In order to develop such empathic social robots, it is important to consider human reactions derived from the interaction with them. Our purpose lies in examining the effects of human-humanoid interaction in humans' cognitive state and emotions, including the way the brain responds to such an interaction and consequently, the degree to which humans can perceive the difference of interacting with robots instead of other human beings. Most of the studies have tried to examine interactive tasks through observation, which means using video clips, or images [2][4], highlighting the limitation of the physical interaction and the loss of the sense of embodiment.

The second step is the determination of the modalities that need to be used for the optimal emotion and perception recognition. Emotional information can be transmitted through verbal (speech and semantic content of a message) and non-verbal (facial and vocal expressions, gestures) communicative tools that can be influenced by several internal or external conditions, like the mood of the person or the environment [5]. However, a multimodal approach is preferred, avoiding the limitations each modality may have. For the purpose of our work, we decided to combine EEG data to include the physiological aspect, with voice detection and self-measurements for the personal and psychological factors.

1.1 State-of-the-art

Researches on emotions have been based on the extraction of two kind of signals: the physiological (i.e the Galvanic skin response (GSR), skin temperature (ST), electroencephalogram (EEG), Heart Rate (HR)) and the non-physiological ones (facial expressions, voice detection and gestures). The early works have been mainly based on the latter and especially face and voice recognition. Physiological signals though, in recent works, seem to have higher accuracy, with EEG being advantageous as the signal comes directly from the central nervous system and it can provide more accurate information about internal emotional states [6].

Studies that have used only EEG for emotion recognition have managed to correlate frequency bands and brains areas with some basic emotions [9][10][12]. Frontal lobe has been shown to be more related to Valence emotions [9]. Moreover, high frequency bands, like beta or gamma, are also related to Valence emotions compared to the lower ones [9][10][11]. In general, Frontal and Parietal areas have been proved to be the most dominant brain areas for emotion detection [11].

To increase the accuracy and the reliability of such estimations, a multimodal data fusion has recently started to be tested. At the beginning, studies started to combine non-physiological signals [7], like facial expressions, with audio features and text-based emotion recognition, while other studies tried physiological signals, like EEG and eye tracking [8]. Recently, data fusion of both kind of signals, like EEG and facial expressions [11] has increased the accuracy of the results.

Most of the studies though, examining human – robot interaction, have been based on the observation of images without a physical interaction. Urgen et al. [4] examined the difference in perception between humans and robots (mechanical and with physical appearance ones), using only EEG recordings for the sensorimotor mu rhythm (8-13 Hz) and the frontal theta (4-8 Hz). Wang et al. [2], one year later, examined such an interaction based on the observation of images of several social interactions with the mechanical robot Nao. In this study, functional Magnetic Resonance Imaging was used, and the outcome was that robot observation leads to lower MTN (mentalizing network) engagement. Thus, interaction between the robot and the human were considered less believable. Recently, Perez-Gaspar et al. worked again with the combination of voice and facial expressions [3], using cameras and a microphone, with real interaction between a small mechanical robot and a human.

One really important aspect is the one that Borst and Gelder [13] examined about how and if the perception during robot- or avatars-human interaction can differ from the one of human-human interaction, regarding the appearance and expressions of emotions. The most important features that can influence the perception are the human likeness, the naturalness of the movements and the emotions expressed by them [13].

There are a lot of studies investigating how the degree of human likeness can influence the perception and the feelings as well as cause differences in brain activity. Cheetham et al. [14][15] found that perceptual discrimination was asymetrical along the human likeness dimension and that familiarity increases with human likeness. Moser et al. [16] found a differentiation in the recognition of emotion provoked by an avatar and photographs of human faces between females and males. Chaminade et al. [17] examined the perception of different emotions expressed by a human and a mechanical robot through video clips, using fMRI. There are also some EEG studies examining differences in the perception while interacting with a human or a robot. Theta oscillations have been studied as they are supposed to be correlated with memory processes and can be used as a dependent measure to investigate responses to visual properties of artificial agents [4]. Regarding the frontal theta oscillations, a significant increase in the activity were found when observing a humanoid robot but not a mechanical one [4]. This suggests that frontal theta activity is modulated by the appearance of the agent being observed.

Lastly, we can mention some examples of some already used robot systems that can integrate emotion recognition for interaction tasks. Robot Kismet [18], and his recent extension Jibo, function as companion for commercial purposes and use voice and facial recognition accordingly. Moreover, MOUE [19] is able to capture physiological signals and gestures through a bracelet and a webcam.

1.2 Research questions

To address the limitations of previous studies and to broaden the field of human-robot interaction, we conducted an experiment with three different types of interaction. Our main consideration is to examine if the brain can perceive the difference between a human and a robot which looks exactly like the human. For that purpose, we used one of the most human-like robots, Nadine and her creator, Nadia Magnenat-Thalmann, and we compared these two conditions with a neutral person.

To constrain as much as possible the subjectivity of the interaction, we introduced 4 specific areas of discussion to all participants.

Table 1. Research questions intended to be answered in this study

Questions to be answered:
Is there a difference in the perception of a human and an identical human-like robot?
How brain reacts to a human-humanoid interaction and what brain areas can play the most important role?
Is there a difference in emotions and motivation when simply interacting with a human and an identical robot?

For the validation and the accuracy of our experiment, that is to properly examine the effect of such interactions, we used EEG recording to capture the brain activity, an audio recorder to capture voice and speech features and psychometric measures through a questionnaire which subjectively examined the emotional states of the participants.

2 Material and Methods

2.1 Participants

Twelve healthy adults (all of the participants were male aged from 20 to 35) participated voluntarily in this study. The subject took place in the Institute for Media and Innovation (IMI) at the Nanyang Technological University (NTU). We tried to ensure no previous experience of the participants with robots to avoid any bias in our results. A form of consent, based on the NTU requirements, was signed by all the subjects before the onset of the experiment. None of them mentioned any sign of discomfort.

2.2 Experimental design

During the experiment, volunteers were exposed to three different types of interaction under the same scenario. The first case (A) constitutes the control case and participants interacted with a neutral person. We chose to put the control case first to avoid any discomfort that might be caused by the interaction with the robot and to enhance the sense of familiarity during the whole process. The second case (B) concerns the human-robot interaction and participants had the opportunity to communicate with Nadine. Nadine is modelled on Prof. Nadia Thalmann, she has very natural-looking skin and hair, and realistic hands, providing a strong human-likeness. We chose to use the interaction with the real identical person as the third and last case (C) to examine if the brain can directly perceive the differences between the two last conditions.

The thematic areas of the discussion were pre-defined and guided by the people or robot involved in the process, but the time of the interaction was up to the participants.

Fig. 1. Participants during the three types of interaction. Left: Case A- Participant with a natural person, Middle: Case B- Participants interacting with Nadine, Right: Case C- Participant discussing with Prof. Nadia Magnenat Thalmann

2.3 EEG recordings and analysis

EEG signals were recorded and amplified using a NuAmps amplifier (https://compumedicsneuroscan.com/applications/eeg/). 34 electrodes were attached on a Quick-Cap according to 10-20 system at the locations Fp, F, FT, FC, C, T, TP, CP, P, PO, O. Curry 8 X was used for the data acquisition and the online processing with a sample rate 1000Hz per channel.

The analysis of the EEG data and the processing of the signal were carried in MATLAB. All data were carefully checked for artifacts, like eye blinks or head/body movements. Fast Fourier Transform was applied to the signal to transport it to the frequency domain and then the power spectra were calculated. The analysis was conducted in two set ups. The first one consists of 5 Regions of Interest (ROI) examining five brain areas: Prefrontal (Fp), Frontal (F), Parietal (P), Temporal (T) and Occipital (O) whereas the second one analyses the same areas but for each hemisphere (10 ROIs). Brain rhythms that we are mainly interested in are theta (3-7 Hz), alpha (8-12), beta (13-30 Hz) and low gamma (30-42 Hz).

Based on previous studies, we will focus our research in the frontal and parietal areas [11] and we will use the occipital region to investigate the recruitment of visual attention mechanisms. We will also consider the existence of frontal theta oscillations that some studies have already noticed during human-robot interaction [4].

2.4 Dialog and audio analysis

The whole conversation was in English. The human participants were from different cultural backgrounds with unique styles of conversation. The thematic areas though were specific no matter the choice of each interviewer. On the other hand, Nadine was operated in two modes: *control* and *free* mode.

Our humanoid in the *control* mode used the Wizard-of-Oz technique and the questions in the interviews were asked in an orderly fashion. The participants had to respond to each of those questions, followed by the free *mode*, where the participant was asked to ask RN anything. In the *free* mode, the answers are based on a chatbot with the architecture in Fig. 2. In our experiment, the episodic memory portion is ignored, since the participant was unfamiliar to Nadine.

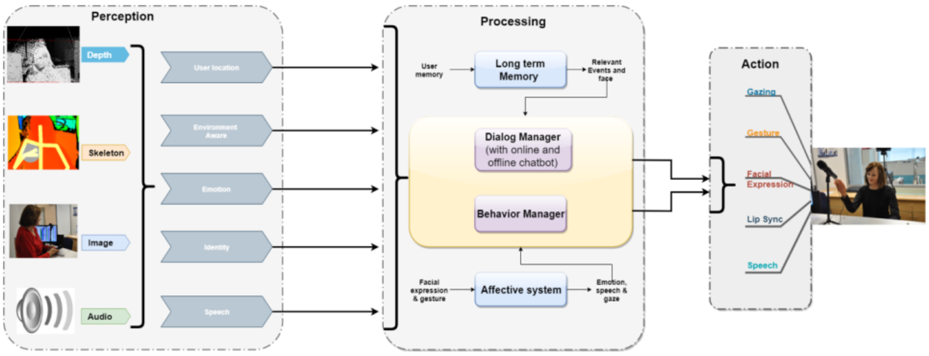

Fig. 2. Nadine's architecture

In our experiment, the episodic memory portion is ignored, since the participant was unfamiliar to Nadine. Therefore, once the speech of the participant is converted to text, it is sent to the chatbot. If the chatbot does not have an appropriate response, it is looked up online. If the online results are not available, a generic default response is given.

2.5 Psychometric data

To provide our results with a higher validity, a reliable and validated questionnaire, including closed-ended Likert-scale questions, was used. The questionnaire consisted of questions regarding participants' demographic data, and mood states for each condition. The mood states scale was based on the Positive and Negative Affect Schedule, which comprises two mood scales: one measuring positive affect and the other measuring negative.

2.6 Statistics

Statistical analysis was carried out for the variables of the EEG and the questionnaire, through JASP. We conducted Repeated Measures ANOVAs and followed up statistically significant results with the Connover's post-hoc tests. When the data did not meet the sphericity requirement, the corresponding non-parametric Friedman test was used.

3 Results

Our first aim was to reveal the dominant frequencies, and consequently, the dominant brain states in different chosen brain areas, examining the possible effects a human-humanoid interaction may have. Moreover, we intended to correlate these frequencies with positive and negative emotions, comparing them with the psychometric and audio results. The purpose of this preliminary study is not to make a proper emotion recognition, but to study the effects human-humanoid interaction can have on human emotional states and behaviors, thus providing a first glance into this new field of research.

3.1 EEG data

As we have already mentioned, we have focused on five brain areas. Thus, for the prefrontal area we noticed a general alpha rhythm, same for all the three conditions, with no significance difference (F(2, 22) = .43, p=0.654). More than any other area of the brain, prefrontal cortex is fully associated with the personality, planning of complex and social behaviors, decision making and in general with the orientation of our behavior in line with our goals and values [20].

Regarding the frontal area, the analyses exhibited statistically significant differences, F(2, 22) = 8.63, p=.002. The post-hoc analyses exhibited that the two human cases differed from the one of the robot, t = 3.76, p=.010 and t = 5.86 for the A vs. B and the C vs. B comparisons, respectively. In both human-human interaction, we noticed a high alpha state whereas during the interaction with Nadine theta oscillations were observed (7.8 ± 0.6 Hz). Theta band power increases as a task becomes more demanding [21]. This can be attributed to the participants' bigger cognitive effort to get focused while discussing with Nadine.

Our results in the parietal area complements the above. A non-parametric Friedman test rendered a chi-square value of 7.45, p = .024. Connover's post-hoc comparisons exhibited that Control and Robot differed from Human, t(22) = 2.97, p=.021 and t(22) = 2.38, p=.053, respectively. In particular, we noticed beta oscillations in both human-human interaction (13.4 ± 3.8 Hz for the A and 14.7 ± 5.5 Hz for the C case) whereas in B case we found a clear alpha state with the 10.8 ± 2.6 Hz. Alpha rhythm in parietal cortex is mostly linked with perception processes [21] whereas beta rhythm is supposed to be an indicator of valence emotions [9].

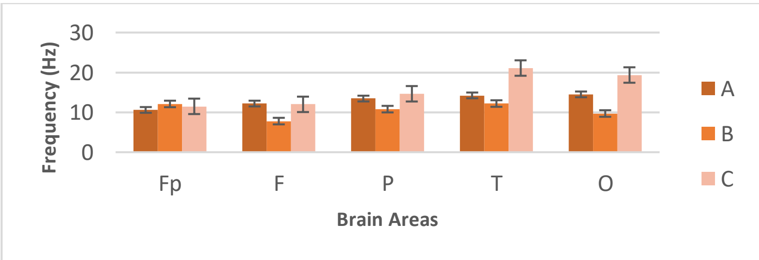

Fig. 3. Mean frequencies observed in each of the 5 ROIs, in response to each case. Power spectra was calculated as $PS = abs(filteredsignal)^{\wedge}2$.

Regarding the temporal lobe we noticed again beta oscillations in both human-human interactions (A: 14.2 ± 4.8 Hz, C: 21.1 ± 5.3 Hz) and alpha in the human-robot case (B: 12.2 ± 2.8 Hz), F(2, 22) = 18.51, p<.001. However, the post-hoc analyses exhibited that case C differed from the case A and B t = -3.95, p = .007 and t = -5.35, p<.001, respectively. Temporal lobe, in general, is associated with processing of auditory information [21]. The presence of the alpha band in the human-robot interaction may indicate that participants put a higher effort to decipher Nadine's speech compared to the human's way of talking they are used to.

Lastly, regarding the occipital region, the analysis exhibited statistically significant differences, $F(2, 22) = 8.06$, $p=.002$. The post-hoc analysis exhibited that Nadine's case (B) presented an alpha rhythm (9.7 ± 2.3 Hz) differed from both A and C cases (A: 14.5 ± 5.7 Hz, C: 19.4 ± 7.6 Hz), $t = -4.26$, $p=.004$ and $t = 2.49$, $p = .090$, respectively. This result was more or less predicted and proves that, from a visual perspective, the brain can completely understand the difference between a human and a robot, whatever appearance the latter may have. The alpha band indicates the recruitment of visual attention mechanisms, which obviously were necessary for the processing of the new features. However, we also notice the higher value of the C case, which reveals a bigger familiarity compared to the A case. That may be explained by the fact that participants had first seen Nadine, so they already had created a memory image of this appearance.

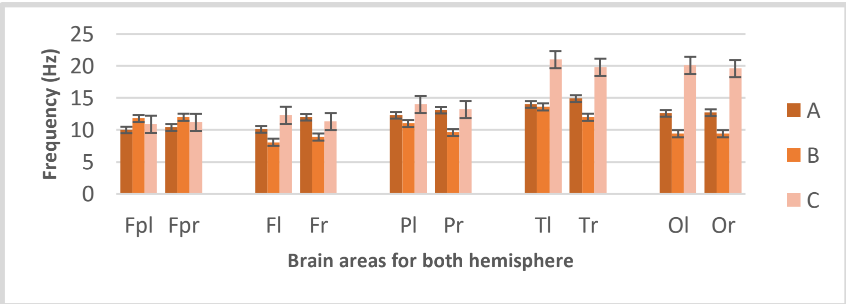

Fig. 4. Mean of frequencies for each brain area for both hemispheres in three conditions

For all these areas, we have also examined possible differences between the two hemispheres, investigating two main questions. Fig. 4 presents the outcome of the first question regarding the differences among the three conditions for each hemisphere.

The second, and probably more interesting question regards the difference of each condition in the two hemispheres. Thus, we run statistical tests for the three cases separately and we concluded to the results depicted in Fig. 5. For the case A, we noticed a slightly bigger activation of the right hemisphere, but ANOVA tests revealed no significant differences between the two hemispheres. For the case B, we noticed exactly the opposite, with the left hemisphere to be in a higher activation. Parametric post-hoc tests showed though significant validity only for the frontal and parietal areas. For case C, we noticed again higher values of frequencies in the left hemisphere, but ANOVA tests revealed no statistically significance.

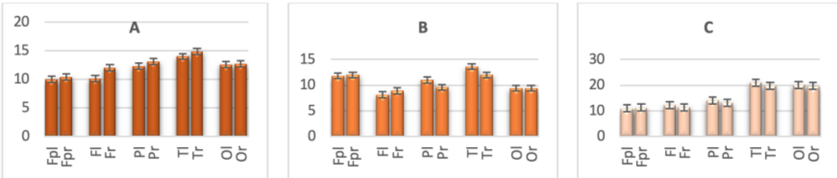

Fig. 5. Differences in frequencies of each case for the two hemispheres

3.2 Psychometric data

Based on our questionnaire we noticed no negative emotions during the whole procedure. The most dominant emotional states were the Interested, Inspired and Confident which reveal also a sense of motivation. It is also worth mentioning that the state of inspiration appears from the case B and on, with an ascending value, which means that Nadine triggered this reaction to the participants, and they kept being inspired for the rest of the procedure. We can also justify this supporting that they found the similarity in the appearance interesting and motivating. The state of the interest is higher in case B which is normal if we assume that people are not yet so used to the existence of robots and they don't often have the chance to interact with them. The state of concentration was rising along the process. Lastly, the participants felt significantly active only in cases B and C. However, in the question of who was the most comfortable to discuss with, participants voted equally the two humans.

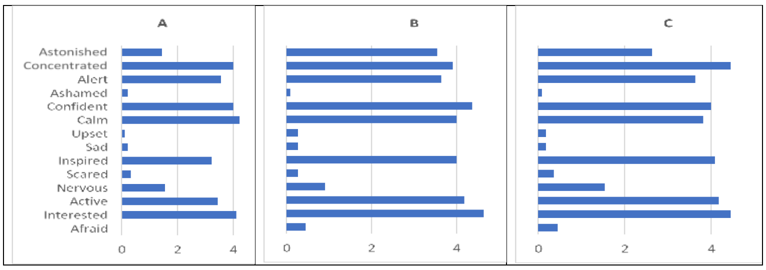

Fig. 6. Participants' emotional states for each condition. The questionnaire was completed at the end of the whole procedure

3.3 Dialog and audio data

We observed that the average pitch of the voice is the highest (133Hz) in the humanoid conversation. Although the small sample size, it seems encouraging to explore the hypothesis where people speak with humanoids in a higher pitch. However, further analysis with more participants is undoubtedly required. In addition, the variable placement of microphone made difficult the comparison of the speech intensity among the participants. Nevertheless, among the questions asked to the participants, there is a peak in the question with regards to belief in the existence of God. This can be due to the emotional nature of the question. This was also verified by our EEG results, as we noticed a higher brain activation during that period of time. There was also noticeable

delay in the speech of the conversation in case C. This is perhaps an indicator of *mirroring* by the participant. With accurate speaker diarization and better microphones, we could do a thorough quantitative analysis in the future.
Of interest is the longer duration of conversation in case C. It is in line with the results we acquired from our questionnaire where participants showed higher amount of inspiration and concentration during that case. We can clearly also see that the duration with neutral human was lower than humanoid that is also verified by the questionnaire results. Lastly, we can note that the conversation with the humanoid had no interruptions by the participant when compared to humans. This highlights the limitation of present generation humanoids which lack natural conversational abilities.

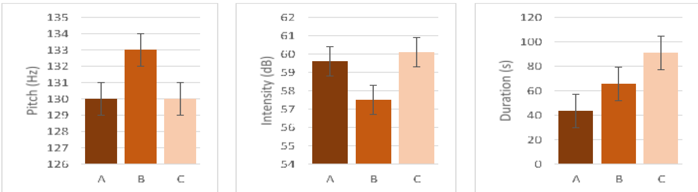

Fig. 7. Mean values for Pitch, Intensity and duration of the interaction for each condition, derived from the audio analysis

4 Discussion and future work

In this preliminary study we investigated the human's perception in human-humanoid interaction and its effects in cognitive and emotional states. We have used three cases where people face three difference types of interaction. To support our research, we have used EEG and audio recordings as well as a questionnaire to complement the above. To the best of our knowledge, there is no previous work that could compare a human with her identical humanoid and provide a physical interaction, supporting new insights in the human-robot interaction and the application of it.

Answering our first research question, our results revealed a difference in the perception of a human and an identical human-like robot mainly in the visual perception. However, this is normal as people are not yet used to interacting and physically seeing robots. This difference was uncovered by the existence of alpha state in the occipital lobe, which proves the activation of visual attention mechanisms compared to the human-human interaction where we noticed the existence of beta states and consequently, the sense of familiarity. The latter was more enhanced in the third case, where the human interacted with the human identical to the robot and thus, we are not sure if this familiarity is a result of the first contact of the person with the robot.

Regarding the brain activity, we concluded to some very interesting results. In the prefrontal cortex, we found no difference between the three cases, all of them synchronized in alpha brain state. However, we noticed frontal theta oscillation in case B, human-Nadine interaction, with a clear difference from the other two conditions where we saw the dominance of alpha state. This comes in line with previous studies [4] that have noted the existence of theta oscillations when a human interacts with a humanoid but not with a mechanical robot.

The same result was observed in the parietal area where, only in the human-robot interaction, we noticed the existence of the alpha state, which is associated with the perception process. In general, we conclude that during such an interaction, humans are unintentionally more concentrated to their tasks and we can attribute that to the existence of new, non-familiar elements people are forced to face. We have previously met this behavior in a previous study [22] where during a comparison between physical and virtual environments, it was found that people tend to unconsciously be more concentrated to environment they are not familiar with. This has also been supported by the results of the questionnaire used, where emotions related to motivational states are developed during the human-robot interaction.

Of great interest is the result of the temporal area, which is linked with the processing of auditory information, and is verified by the outcome of the audio analysis. We noticed the presence of the alpha power only in case B which can be attributed to a higher cognitive effort participant made to understand Nadine’s voice. This can also be correlated with the higher pitch of the voice participants presented during their interaction with Nadine. It could also be a result of nervousness, but the results of the questionnaire didn’t reveal any negative emotion.

We answer our third research question indicating that there is a motivation enhancement throughout our process, with no observation of negative feelings. Participants, in the beginning, were presented as calm, confident and concentrated and while interacting with Nadine new states appeared like inspired, active and interested. The values of all the emotional states were ascending, revealing the high level of motivation. The increasing duration of speech in the three scenarios verifies the same.

To sum up, we remind that the purpose of this study was to provide a first glance of this innovative approach of human-robot interaction and not to execute a proper emotion recognition. The latter is our upcoming goal with which we intend to address any limitation this preliminary work had. Robots and virtual characters are increasingly becoming ubiquitous in our daily lives. Therefore, it is paramount to study our behaviour and emotions to these technological transitions to aid in their humane development and to enhance their applications in several domains like education, rehabilitation or even entertainment.

Acknowledgments

This research is partly supported by the BeingTogether Centre, a collaboration between Nanyang Technological University (NTU) Singapore and University of North Carolina (UNC) at Chapel Hill. The BeingTogether Centre is supported by the National Research Foundation, Prime Ministers Office, Singapore under its International Research Centers in Singapore Funding Initiative. This research is partly supported by the European Commission through the project MINGEI.

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