Preprint Version. Manuscript submitted to and accepted by 2019 International Conference on Cyberworlds.

Detection of humanoid robot design preferences using EEG and eye tracker

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***Abstract*—Currently, many modern humanoid robots have little appeal due to their simple designs and bland appearances. To provide recommendations for designers and improve the designs of humanoid robots, a study of human's perception on humanoid robot designs is conducted using Electroencephalography (EEG), eye tracking information, and questionnaires. We proposed and carried out an experiment with 20 subjects to collect the EEG and eye tracking data to study their reaction to different robot designs and the corresponding preference towards these designs. This study can possibly give us some insights on how people react to the aesthetic designs of different humanoid robot models and the important traits in a humanoid robot design, such as the perceived smartness and friendliness of the robots. Another point of interest is to investigate the most prominent feature of the robot, such as the head, facial features, and the chest. The result shows that the head and facial features are the focus. It is also discovered that more attention is paid to the robots that appear to be more appealing. Lastly, it is affirmed that the first impressions of the robots generally do not change over time, which may imply that a good humanoid robot design impress the observers at first sight.**

Keywords-EEG; eye tracking; design preference; workload recognition; emotion recognition

I. INTRODUCTION

To develop social humanoid robots, an optimal appearance is necessary for human robot interaction (HRI) [1]. Consumers tend to place a lot of emphasis on outer appearances of an inanimate object. However, many modern humanoid robots have little appeal due to their simple designs and bland appearances. Hence, investigation of how people perceive different humanoid robot designs and how much they like them based on appearance is essential for designers. The traditional method of understanding human perceptions is questionnaires, which could pose a risk of subjective bias. Biosignals such as Electroencephalography (EEG) and eye trackers could be considered as a more objective way to understand the true perceptions of the viewers. By combining EEG and eye trackers, it is possible to get an insight of the affective states of the viewers when they are looking at different robot designs, areas of interest in the humanoid robots designs, etc.

In this paper, we conducted an experiment to investigate human responses to the appearances of humanoid robots. 20 subjects are recruited in the experiment. EEG, eye tracker, and questionnaires are used to detect the preference pattern of the subject. The paper is constructed as follows. In Section II, review on eye tracking, EEG, and the application of these two technologies in design area is done. In section III, the experiment setting is described. Section IV presents the hypotheses and section V shows the results. Finally, section VI concludes the paper.

II. RELATED WORK

A. *Eye Tracking*

Eye tracking is an eye sensor technology that detects the eye movements and eye positions to a high level of precision. It captures the state of presence, attentiveness or other mental states from eye data alone. This information can be further analyzed for deeper insights into consumer behaviours such as online shopping or design-based activities such as user experience interfaces.

Fixation and gaze points are the most commonly used features in eye tracking. Gaze points constitute the basic unit of measure – one gaze point is equivalent to one raw sample captured by the eye tracker [2]. A fixation is the state of maintaining the gaze on a singular location, forming a fixation duration of focused view on a specific object. The fixation duration usually ranges from 100 – 300 milliseconds [2]. The number of times such fixations are formed is called the fixation count. The quick and simultaneous eye movements between fixations are known as saccades [3]. Eye tracking can also provide heat maps in either static or dynamic aggregations of gaze points and fixations. The heat map shows the distribution of visual attention [2]. By utilizing a simple colour-coding scheme, heat maps serve as an interpretation of the frequency of viewing spots in specific regions – with red areas indicating a high number of gaze points (implying an increase in viewing interest), yellow areas showing a medium number of gaze points (implying mild viewing interest) and green areas showing few gaze points (implying a less engaged viewing interest). Areas without coloring are not likely to be visited. Another feature of eye tracking is areas of interest (AOI), which is user-defined subregions of a displayed stimulus [2]. It is useful for comparing different groups of participants, conditions, or features within the same scene.

B. EEG

Electroencephalography (EEG) is a non-invasive technique to record the electrical signals generated by the brain via electrodes attached on the scalp surface. It is traditionally used in medical area to detect certain diseases such as seizures. Recently, with the development of affordable and convenient EEG devices, this technology has been applied to various areas, such as neurofeedback training for healthy adults [4], human factors study [5, 6]. Different mental states can be recognized from EEG. For example, in [7] and [8] subject-dependent algorithms for emotion and workload recognition from EEG signals are proposed. For emotion recognition, the accuracy of 3 emotions is 72.22%, while for workload recognition, the accuracy of 4 workload levels is 74.23% [9]. With such mental states identified, evaluation of the qualification for maritime trainees while they were performing maritime tasks is done in [5], investigation of the air traffic controllers' reaction to future workplace is studied in [6]. In this paper, the algorithms in [7] and [8] are employed to identify the mental states from the EEG signals.

C. Evaluation of humanoid robots design

Humanoid robots have great potential to lead the way in the next industrial revolution, especially as a companion in medical, retail and education. A lot of research and development have been done to improve the performance of the robots but less so on its aesthetic appeal. Although emphasis should be placed on the functionality of a humanoid robot design, its aesthetic appeal should not be neglected, especially if the robot is supposed to be customer-centric since its appearance forms an integral part of the user experience [1].

Experiments have benchmarked the traits of a humanoid robot such as its perceived aesthetics, perceived affordances like smartness and the use intentions. An extensive experiment was done to evaluate the use of such standardized measurement tools in human robot interaction (HRI) [10]. Another experiment highlighted the aesthetics and behavioural impact of robots in different social settings [11].

However, the evaluation is done mainly based on the user's subjective ratings and lack of objective measurements such as using EEG to get the brain reaction towards the robot design, making the findings presumptuous. Measurement of the aesthetics of humanoid robots based on EEG data from the brain processes, eye movements as well as personal perception could greatly increase the validity and accuracy of the findings by mitigating subject biasness.

There are some existing work using either EEG or eye tracking to study the aesthetic preference in the design area. For example, [12] found that both EEG and eye movements can indicate one' affective responses towards aesthetics of an object such as abstract art painting [12]. [13] proposed a novel system measuring user aesthetics on virtual 3D shapes with motion using EEG signals. They captured the EEG signals when users were viewing 3D bracelet shapes and decomposed them into alpha, beta, theta, gamma and delta rhythm. An accuracy of 80% was achieved for two-class classification on likeness and dis-likeness by using K-nearest neighbors classifier. [14] used EEG to analyze users' preferences on images for the purpose of designing a cultural product. They found that the frontal alpha asymmetry could be used as reflection on users' pleasure degree when viewing different cultural elements. The EEG signal has also been used to quantify the aesthetic sentiments about clothing [15]. The interactions between sentiment dimensions and event-related potentials were studied towards aesthetic evaluation of clothing using EEG. [16] used EEG to evaluate the emotion responses to the visual art and commercial stimuli. They collected 80 artistic colored paintings as visual art stimuli and 80 window displays for fashion collections. Their results showed positive emotion responses to the visual art stimuli in regard of aesthetics, while favorable emotional responses were observed on commercial stimuli conceived as beautiful. [17] performed a preliminary study on using EEG signals to evaluate users' first impression on an interface. Their results showed that users' first impression of the design about usability and aesthetics are formed within less than 1000ms period, which starts from perceiving visual details and ends with aesthetics evaluation. A methodology to evaluate visual aesthetics in product design was proposed in [18]. The methodology is based on eye tracking data including the number, duration and coordinate of eye fixations from more than 300 participants and it was validated on 200 participants. The method was able to quantify and predict aesthetic preferences with only eye tracking data. Another study [19] proposed to use eye-tracking data to evaluate user preference on instant message applications. Four aspects of visual aesthetics including simplicity, diversity, colorfulness and craftsmanship were evaluated based on people's gaze patterns in [20]. 23 participants were invited for viewing three kinds (high, neutral and low appealing) of websites. Their results showed that fixation and saccade of eye tracking data could be used as indicators of aesthetics in these aspects. [21] combined EEG and eye tracking for optimizing design of user interface. They tested their method on optimizing the UI of a music player and proved their method could evolve towards optimized aesthetic design based on users' preferences.

Considering the benefit of eye tracking and EEG technique, in this paper, we integrate and complement the use of various technique such as EEG, eye tracking, and traditional questionnaires in our study to detect the preference of robot design.

III. Experiment

A. Subjects

Twenty participants, between the ages of 21 to 24, were recruited for the experiment. The participants consist of 17 males and 3 females, 17 of whom have no background in Art and Design, 3 with a little background in Art and Design.

B. Device

The device for EEG data recording used in the experiment is the Emotiv Epoc with 14 channels (AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2) [22]. It has a sampling rate of 128 Hz. For eye tracking, the Tobii Pro X3-120 is used, which has a gaze sampling rate of 120 Hz, providing extensive and detailed eye tracking data [23].

C. Procedure

Firstly, the subjects were briefed about the experiment and asked to sign the consent form. Then the calibration of eye tracker and EEG for emotion recognition is done for each subject. After all preparation, the actual experiment started. There are in total three stages: in stage 1, the participants observed 12 images of humanoid robots (Fig. 1) briefly for 5 seconds each to rate their first impression of the robots based on likability. The rating is on a scale ranges from 0 to 9, where 0 is the least level of likability and 9 is the highest level of likability. In stage 2, they further observed each robot carefully for 10 seconds each and rated them individually based on these specific metrics: smartness, friendliness, and second impression based on likability. In stage 3, they chose the top 3 robots from the collage of the 12 robots and proceed to the post experiment questionnaire. The post experiment questionnaire includes questions such as "How important is smartness/ friendliness/ likability in selecting the best robot design?" "How much does the head and facial features/body features/body shape affect your selections?". The EEG data as well as the eye tracking data are recorded throughout the experiment.

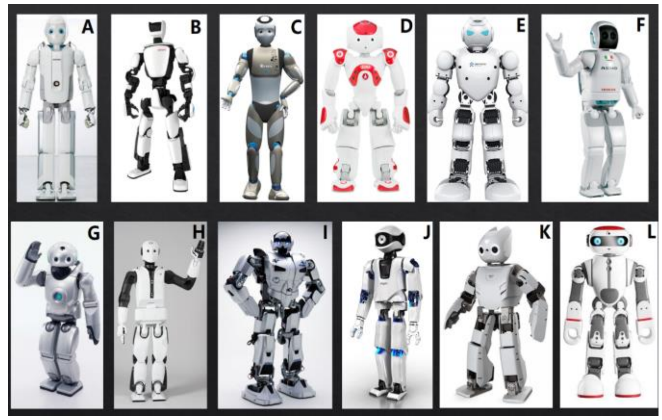

Figure 1. Humanoid robots in the experiment.

IV. Hypothesis

The objectives of this study is to investigate whether there are any difference between the first and second impression of the humanoid robot designs; to understand the preferences of the humanoid robots based on their characterizations; to detect the viewers' preference towards different robot design based on eye tracking data and EEG data. Thus, there are mainly four hypotheses to achieve this objectives.

H1: It is hypothesized that the face is the most prominent feature of a robot.

If it is indeed verified that the face draws the most attention, designers can place more focus on the facial details to further improve a humanoid robot design.

H2: It is hypothesized that first impression of the robots generally does not change over time.

A good first impression is essential due to it being the first information a viewer can derive from the robot. If the viewer is impressed by the initial outlook of the robot, he or she will be keener to initiate further interest towards the robot.

H3: It is hypothesized that participants who take longer time to select their top 3 robot designs have a higher average workload in stage 3 generally.

This hypothesis tests the relationship between decisiveness and the cognitive effort to make the decisions. It shows how the selection process can affect different people and the effects of their thought processes.

H4: It is hypothesized that more attention is paid to the robots that the participants like more during the cross comparisons in stage 3.

This hypothesis tests the amount of attention placed on certain designs. If the designs attract the most views from eye tracking data, these designs are the one that the viewers like the most.

V. Results and Discussion

A. Prominent features in robot design

The subjects were asked to rate the importance of smartness, friendliness, likability in selecting the best robot design and how much head/facial features, body features, body shape affect the selection. From the questionnaire, it shows that likability is most important factor, whereas friendliness is the factor with the least importance. For the influence of the appearance features, the subjects rated that the head/facial features are slightly more important than the body feature. From the eye tracking data, the fixation counts and mean fixation duration in both stages 1 (Fig. 2 and 3) and stage 2 (Fig. 4 and 5) indicate that the face and chest are the main sources of attraction as compared to other body parts such as the arms and legs. Generally, the chest has higher fixation counts as compared to the head, while the head has a higher mean fixation duration as compared to the chest. Hence, the hypothesis H1 for the face being the most prominent feature of a robot is partially affirmed.

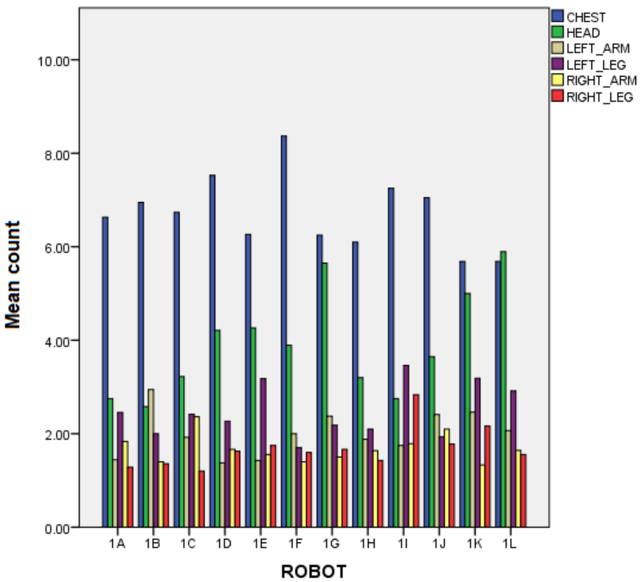

Figure 2. Fixation count in stage 1 of each robot.

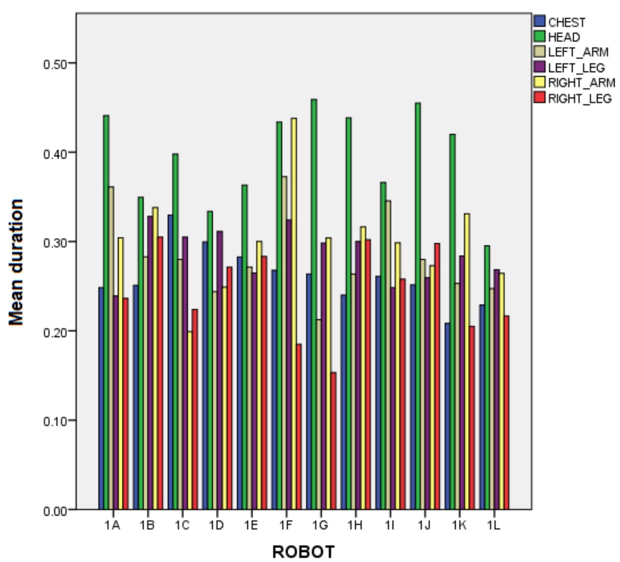

Figure 3. Mean fixation duration in stage 1 of each robot.

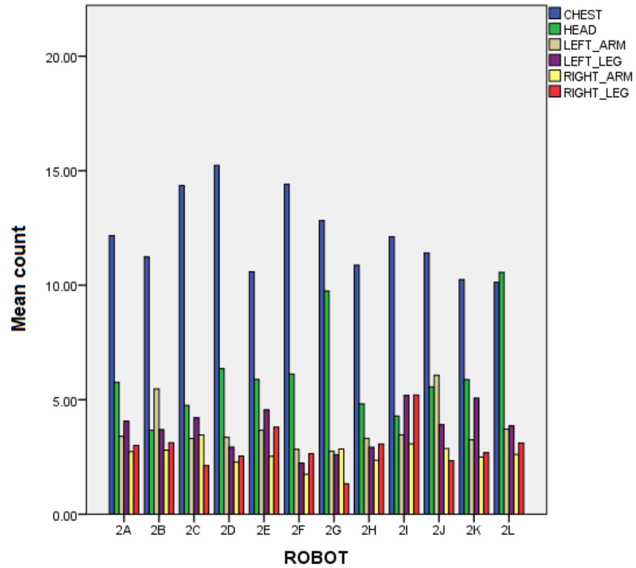

Figure 4. Fixation count in stage 2 of each robot.

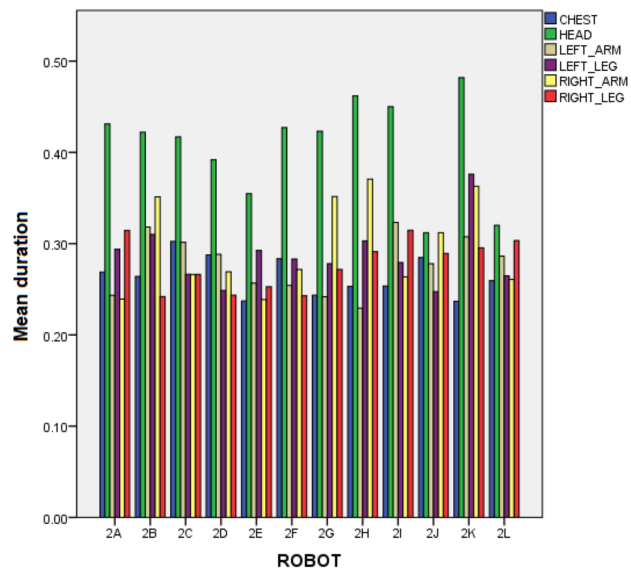

Figure 5. Mean fixation duration in stage 2 of each robot.

B. First impression vs second impression

In Table I, the rating of likability for first impression (stage 1) and second impression (stage 2) derived from the mean values of the questionnaire answered by all 20 participants are presented in Table 8. The scale of the rating ranges from 0 to 9. The emotion states of the subjects when they were viewing the robot designs in stage 1 and 2 are recognized from EEG using the algorithm in [7]. The average of EEG-based emotion recognition results for stage 1 and stage 2 are also tabulated in Table 8 for comparison. The mean emotion values range from 0 to 2. Two-tailed pair t-test is applied to the likability rating and EEG-based emotion recognition results, and it shows no significant difference between the first impression (stage 1) and second impression (stage 2). Thus Hypothesis H2 is confirmed.

TABLE I. LIKABILITY AND EEG-BASED EMOTION RESULTS FOR FIRST AND SECOND IMPRESSION

Robot Design	Likability rating from subjects		EEG-based emotion recognition	
	Stage 1	***Stage 2***	***Stage 1***	***Stage 2***
A	5.45	5.05	0.98	1.11
B	6.65	6.45	1.12	1.02
C	5.35	5.6	1	1.14
D	5.45	5.2	1.1	1.22
E	5.75	4.3	1.12	1.1
F	6.1	6	1.17	1.25
G	4.8	5.05	1.18	1.14
H	4.65	4.65	1.3	1.17
I	6.75	6.25	1.32	1.06
J	5.1	4.15	1.11	1.25
K	6.55	6.6	1.17	1.12
L	4.8	4.7	0.95	1.17

C. Mental workload in selection of robot design

The correlation between EEG-based emotions, workload, and time spent in choosing the top 3 robot designs in stage 3 is calculated and presented in Table II. The workload is recognized from EEG signal using the algorithm proposed in [8]. However, no significant correlation is detected. Thus, hypothesis H1b is not affirmed which may indicate that there are other factors that influence the time taken to choose the top 3 designs and workload may not be a reliable indicator of decisiveness displayed in the selection process.

TABLE II. CORRELATIONS BETWEEN EEG-BASED EMOTION, WORKLOAD, AND TIME SPENT IN STAGE 3

		EEG-based workload (Stage 3)	Time spent (Stage 3)
EEG-based workload (Stage 3)	Pearson Correlation	1	-0.03
	Sig.	-	0.918
	N	20	20
Time spent (Stage 3)	Pearson Correlation	-0.03	1
	Sig.	0.918	-
	N	20	20

D. Eye tracking results in selection of robot design

Among the twelve designs, robot I is the top design according to the subjects' selection choices in the questionnaire. Robot K and B are the next two top choices as evident from their high selection frequencies.

From the eye tracking data collected in stage 3, robot B has the highest fixation count of 24.9, while robots K and I has the next highest fixation count at 19.1 and 18.6 counts respectively. Robot B also has the longest total fixation duration at 5.76 seconds followed by robot I at 4.92 and K at 3.96 seconds. It is further supported by the heat map shown in Fig. 6. In summary, we can infer a general direct relationship between the amount of attention paid to a design and the preference towards it. Hence, the hypothesis H4 is confirmed that more attention is paid to the robots that the participants like more generally.

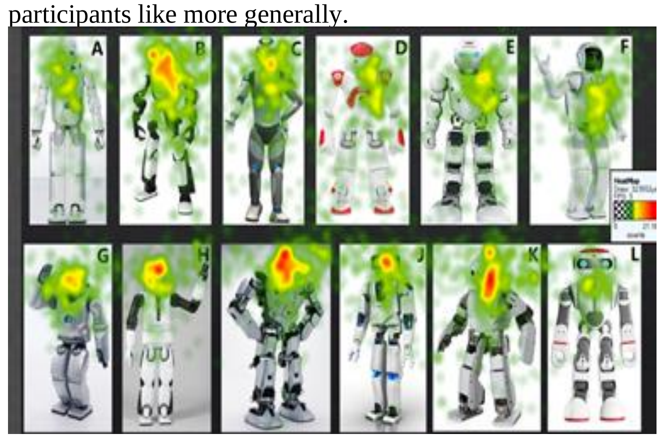

Figure 6. Cumulative heat map for all 20 participants in stage 3.

VI. CONCLUSION

In this study, we proposed and carried out an experiment to study the preference of robot design using biosignals such as EEG and eye tracking. 20 subjects took participated in the data collection. As a result, we found out that a good humanoid robot design impresses the consumers at the first sight and the head/facial features are the most prominent features. The first impression of the robots generally does not change over time. However, it is not clear if workload is a reliable indicator of decisiveness in the design selection process. More attention is paid to the robots that are finally chosen.

The proposed algorithm consisting of both EEG and eye tracking can help a subject make choices of the robot designs based on his/her brain activities and eye movements. For example, this could be helpful in the field of design to make decisions based on preferential selection in a more intuitive way. The results can also help researchers and designers to study the effects of humanoid robot designs on the human mind that can aid them to develop better looking humanoid robots in the future.

Currently, this study on humanoid robots is only limited to a few factors such as friendliness and smartness, there are other influential factors that we can explore such as realism and familiarity [1]. Product designs other than humanoid robots can be studied in a similar manner as well.

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