Are you really angry? Detecting emotion veracity as a proposed tool for interaction

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ABSTRACT

Interaction with faces expressing emotion is compelling and can focus human attention strongly. A face showing emotion reflects the internal mental state of the displayer of the emotion and is arguably also an attempt to influence the internal mental state of the observer of the displayed emotion.

We found that pupillary response patterns can predict the veracity of anger better than the verbal response of the same individual participants. This supports the previous claim for such a result for smiles, from the results on another emotion, anger.

Given the significant differences in behavioural responses expected from the literature on smiles versus anger, the unexpected similarity of results suggests that this method could be used in general for detecting the veracity of many emotions. Even using just smiles and anger, we propose that virtual reality or screen avatars expressing such emotions to cajole, brow beat or otherwise enveigle co-operation in settings such as chronic condition management or aged care, could be substantially improved if we can measure the actual perception of the veracity of emotion felt by human beings.

CCS CONCEPTS

• **Human-centred computing** → **User studies** • *Computer systems organization* → *Sensors and actuators* • Applied computing → Health informatics

KEYWORDS

Affective computing, emotion veracity, anger recognition, eye gaze, pupil dilation, pupillary response, physiological signals, machine classification.

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1 INTRODUCTION

Acted anger expressions, whose expressors do not carry genuine feeling, attempt to manipulate the perceivers of their acted anger. This study aims to examine empirically how well humans are capable of consciously detecting the veracity of anger, and further, their non-conscious ability to do so, as reflected in their pupillary responses. In this study, genuine and acted anger stimuli are differentiated based on the source of the stimuli.

The experiment collected 22 participants' verbal response and their pupillary response in viewing two types of anger stimuli. The results showed significant improvement from the accuracy of human verbal response (60%) to the accuracy of ensembles of machine classifiers trained on pupillary responses (95%). This result directly parallels our results for smiles [9], which we did not expect from our review of the literature on anger and on smiles. This study shows that by using emotion perceivers' physiological signals, machines can reach high accuracy in differentiating genuine and acted anger.

Our method can be used to better understand human reactions when computer avatars or fellow humans display an angry or smiling expression in a virtual or computer mediated environment. This inverts and complements the use of emotion [2], user affect [10], and the fundamental application of affective computing in HCI to track user affective state for corresponding feedback [24]. Further, human robot interaction is likely to be facilitated by human-like facial expressions [16] – but will we feel the robots are expressing real emotions? If not, our emotional reactions are likely to hinder appropriate interactions.

2 EMOTION DETECTION THROUGH PHYSIOLOGICAL SIGNALS

Physiological signals have natural advantages for computerised control [24] and classification tasks. They are independent of conscious human control, and so less likely to be affected by subjective biases.

Recently [13] investigated physiological signals for emotion conveyed in audio. The accuracy was 95% in classifying emotional content of songs. Nevertheless, it is unclear whether the physiological changes were caused by recognising the emotion intended by the artists or recognising participants' own emotional experience to the music, as physiological signals were recorded directly from participants.

Progressing from recognising basic emotion states, differentiating genuine and fake emotion is gaining attention. Increasing numbers of empirical studies have indicated that for those expressing genuine and fake emotion, their physiological signals are sufficiently different to be promising for machine classification [11, 14]. In light of [13]'s work, studying those who *perceive* genuine and fake emotion may be another direction for machine classification of genuine and fake emotion.

Most recently we [9] used perceivers' physiological signals in detecting genuine and posed smiles from participants who perceived (watched) smiles. The accuracy of human verbal responses was 59%, while the machine classification was 94%. The smile stimuli were collected from three benchmark databases. The videos containing elicited smiles were treated as genuine smiles while those professionally acted were treated as posed smiles. The materials were then processed into stimuli, considering colour, length, size of video and so on. This study adopts a similar analysis approach.

2.1 Anger and its authenticity

Humans are quicker to detect angry faces in comparison with upset and happy faces, and [17] suggested it to be an evolutionary mechanism in reaction to facial expressions cuing for threats.

Many people seem to believe that making use of this compelling emotion, anger, is likely to manipulate their opponents and distort situations to their advantage, yet [3] found that humans can sense the authenticity differences between surface and deep acted anger. The surface anger stimuli were recorded by an experienced actor only displaying the expression, while deep acted anger stimuli were recorded when the actors were instructed to express some genuine anger by "recall[ing] an event that had truly made them feel angry". The use of anger was undermined when it is deemed less authentic, and is more likely to produce disrupted trust between two parties [3]. Though they did not examine the degree of accuracy, their work suggests that humans are capable of consciously judging these two types of anger.

Then, [4] examined adults' ability to discriminate the authenticity of emotion displayed in still image stimuli and found that adults have similar ability to determine the authenticity of happy and sad faces. In both of these, the accuracy was higher than chance. Though it is possible that human treat all danger cues, like fearful faces, equivalently to avoid any danger, [4] pointed out the possibility that static stimuli may fail to mimic the physical dynamics of real expressions. We could not find any results in the literature for human discrimination of the authenticity of the anger (or any similar negative emotion) using dynamic video stimuli.

2.2 Stimuli collection

We could find no benchmark datasets with genuine and acted anger, so some initial work was needed to collect a suitable corpus for experiments.

Genuine and acted anger were differentiated based on the sources of the videos. Genuine anger stimuli were videos clips of live news reporting and documentaries, where it is implicit or explicit that these were verbatim recordings. Acted anger stimuli were taken from cuts of movies, which are clearly acted. Thus, 10 genuine anger and 10 acted anger videos were chosen in total.

All videos were obtained from YouTube, and selected manually based on identifiable and reputable sources. There was no contact possible with the protagonists in the videos, therefore it was not possible to determine if our acted anger category corresponds to deep acted anger and surface acted anger respectively, as in the work of [3].

The videos were chosen to maintain similar variations of age, ethnicity, cinematography, background colour / complexity, intensity of anger, degree of body movement particularly verboseness of protagonists in the videos, thus mimicking the variations of anger emotion expression in social interaction. The likelihood of observers being able to differentiate videos based on the context is largely eliminated by these selection criteria. The length of videos used are appropriate under fair use for research purposes. The actors in the acted anger videos are not famous, nor familiar to the authors or experiment subjects, e.g. see Fig. 1.

The videos were trimmed to anger expressing scenes, lasting for 1 to 2 seconds, then cropped in size to display head regions only, thus minimising backgrounds. Videos were converted frame by frame to grayscale. Each frame was then standardised for brightness and contrast values, to make them visually comparable to the original coloured versions, and similar across videos. This is to minimise the impacts of environment light changes on the pupil size, as it is much more straightforward to consistently normalise the luminance in grayscale rather than across 3 RGB channels. The pupillary response has a primary purpose to control the quantity of light reaching the retina, so controlling luminance removes a significant possible confounding factor.

2.3 Experiment design

The 20 videos were displayed in 20 different sequences. The sequences were constructed by the use of a Latin square to achieve a balanced order for video presentation sequence, to control for order effects [23]. That is, each video is seen first by one participant and last by another and so on. In this way, effects found will not be compromised by order of stimuli presentation.

The video stimuli play when the page containing it is loaded, and a time stamp written to the data output file, for physiological signals analysis. After the video, a question was presented for participants' responses. The question was to collect the selection the participant made consciously as to the genuineness or otherwise of the anger shown in that video. A still image is shown in Fig. 1, with an example stimulus of acted anger.

Figure 1. A sample stimulus

Then, participants were asked 3 further question on the next page. The 1^{st} question assessed their confidence level as to genuineness or otherwise using a 5-point Likert scale. The 2^{nd} whether they had recognised the video. If they answered yes to the 2^{nd} question, the 3^{rd} question asked if recognising the video impacted on their decision. These two questions were asked since the acted anger stimuli were sourced from movies, there was some possibility that a participant would have seen and recognised the clips, and immediately known that the anger was acted. Alternatively, by sheer chance, they may have seen the same YouTube clip containing the genuine anger scenes.

2.4 Hypotheses

Based on humans' sensitivity to the authenticity of anger, as reviewed in the literature survey (see §2.1 for details), the accuracy of verbal response is expected to be high.

Pupillary responses are expected to be significantly different when viewing genuine and acted anger stimuli. Considering related work [8, 9], pupillary response would be stronger to acted anger stimuli, and thus trained classifiers can be expected to result in a higher accuracy as compared to human classification.

3 RESULTS AND DISCUSSION

3.1 Participants

The participants were 22 university students recruited using our University's research participation scheme. There were 15 Female, 7 Male; 18 Westerners 4 East Asians with valid pupillary responses. We excluded some participants due to a faulty eye tracker, and some glasses wearers with intermittent data loss. The mean age of the 22 participants with valid pupillary responses was 19.7 with standard deviation of 3.3 years. Each participant had a normal or corrected-to-normal vision, and provided their written consent prior to their voluntary participation. The experiment was approved by the Australian National University's Human Research Ethics Committee.

3.2 Procedure

The experiment was conducted in the same location in the same laboratory (See Figure 2). Participants were given oral instruction by the experimenter prior to the experiment. After sitting on the chair, they were asked to put on an Empatica E4, measuring skin conductance and blood volume pulse, and heart rate [6] on the wrist of their non-dominate hand. Eye gaze and pupil size were tracked by a remote Eye Tribe eye gaze tracker at 60 Hz [20].

Participants performed an eye gaze calibration as to increase the quality of the gaze tracking data recording, and were asked to perform the experiment on the computer. On completion of the computer tasks, they were briefly interviewed by the experimenter as to how they consciously identified genuine or acted anger in their answers to those questions during the experiment.

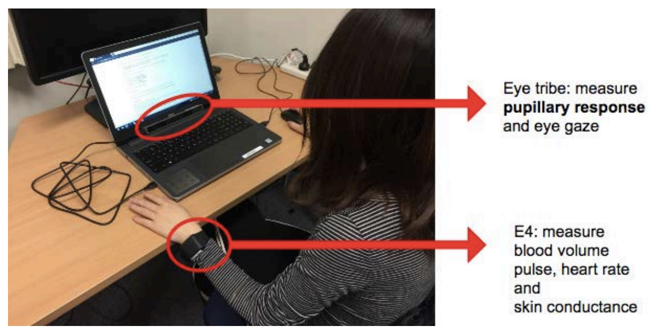

Figure 3. The experimental setup

3.3 Results

The mean accuracy of selection responses (subsequently called *verbal* responses or conscious discrimination) over 22 participants is 60% with standard deviation of 0.2%. In this experiment, the mean accuracy is compared against chance, which is 50% as there were two options for the participants over balanced numbers of stimuli. The 60% result is only moderately higher than chance.

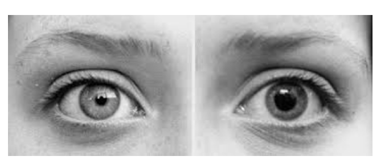

Figure 2. Pupillary response reflects luminance, cognitive

In order to analyse the differences of participants' conscious judgements statistically for each condition, a two paired sample t-test was performed on the accuracy of discriminating genuine and acted anger over the 22 participants. The p-value (two-tail) was 0.35. This revealed that there is no significant difference in the accuracy for conscious discrimination of either genuine or acted anger.

The pupillary response, which is the primary physiological signal we use in this study, is illustrated below in Fig. 3. This is a demonstration of different sizes of two pupils belonging to the same person [5]. Please note that a human being with two pupils with such different dilation in a real situation would be suffering from concusion or another severe neuro-logical condition.
The pupillary response was calculated from each individual's pupil sizes obtained from the eye tracker while they viewed each video. Pupil size data was normalised across all videos of each participant, since the significant signal is the variation in the size of the pupil, not its magnitude.

The occasional eye blink returns a pupil size of zero for those frames. These values were corrected by linear interpolation between the nearby (earlier and later frames') nonzero values. Then, the corrected pupil size values were averaged between the two eyes, which returned a single value for each recorded frame. The pupil size values for all participants were averaged for each recorded frame to produce a visualisation of the overall result.

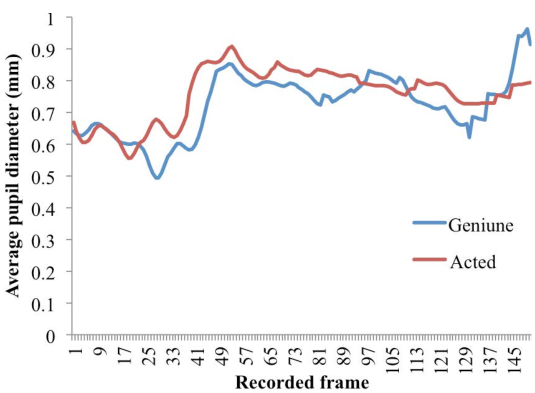

Figure 4. Pupillary response to genuine versus acted anger stimuli over the time course of the recorded frames for the 22 participants

Visually, the normalised mean pupil diameter (PD) data across 22 participants started similarly for both genuine and acted in terms of pattern and y values. They then diverged, changing to the opposite directions for genuine versus acted anger at around frame 22. The PD converged into mostly similar paths at around frame 47. This suggests these two frames may be two key points for the beginning of human non-conscious discrimination.

Further, pupil dilation shows a stronger response to acted anger, as revealed in Fig. 4, where the curve representing acted anger is generally above the genuine anger curve. This may be a direct effect of recognising acted anger, an effect of cognitive load [12] if it takes more processing to recognise acted anger, or 'liking' entertainment – given the sources of our acted videos – but we believe this is unlikely on well cropped 2 second videos.

In order to analyse the difference statistically, a Kolmogorov-Smirnov (KS) test was performed on the value in viewing two types of anger over 22 participants. This test is to analyse differences in both location and shape of the empirical distribution functions of the two sets of samples [15]. There was a highly significant difference of pupillary response to genuine and acted anger ($p = 0.0012$). Overall, this is a clear indication that the pupillary response is useful for machine classification.

3.4 Discussion

The results for pupillary response trained machine classifiers (replicating those used in [8]) can reach a much higher accuracy, compared to human verbal response. The amount of improvement in accuracy is highly similar to [9], see Table 1.

Table 1. Mean accuracy comparison between genuine and acted anger detection and real and posed smile detection

	Anger	Smile [9]
Verbal response	60%	59%
Pupillary response	95%	94%

The similarity to smile results is unexpected, given the literature indicating that the ability of humans to consciously detect anger on faces is much faster compared to smiles on faces, which indicates a higher sensitivity to anger [17]. This identifies a gap in the literature, in that while detection of anger on faces may be quicker, but it is clear that the ability of human conscious and non-conscious authenticity discrimination for anger and smiles is essentially the same.

The strong similarity in pupillary response to acted anger, similar to smiles in [9], appears to contradict the findings of [4], who suggested that the ability to detect fake negative emotion is an outcome of social development, so we would expect different responses when the anger is acted.

4 LIMITATIONS

Our acted anger videos may be a mix of surface acted and deep acted anger. Since our results can differentiate our acted anger and genuine anger with 95% accuracy from the pupillary responses, this shows that even if our acted anger category is such a mix, they are both clearly different from genuine anger.

It is possible that participants could recognise differences in backgrounds or in cinematographic quality, notwithstanding our efforts. Our results strongly parallel previous results on smiles [8, 9] where benchmark datasets were used, where this could not have been the case, giving us some confidence that this is not the case in this work.

5 CONCLUSIONS AND FUTURE WORK

In summary, our study showed that by using emotion perceivers' physiological signals, machines can reach a high accuracy in differentiating genuine and acted anger. Further, this could be fellow humans display an angry or smiling expression in a virtual environment. This is a setting in which the use of machine learning directly on the videos is unlikely to be useful [1, 7].

Our future work will involve investigating sequencing effects in comparing verbal responses and detection from physiological signals from our participants using AI techniques such as neural or fuzzy [18, 22], the use of avatars expressing anger – where a computer system generates an avatar, then its behaviour is part of HCI, and its emotional realism is part of the interface — and impacts user performance [19, 21]. Finally, we recorded participants' skin conductance and blood volume pulse, these results will be reported in a subsequent paper.

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