Support Vector Machine Tuning for Improving Four-Quadrant Emotion Prediction in Virtual Reality (VR) using Wearable Electrodermography (EDG)

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Abstract. Electrodermography (EDG) / Galvanic Skin Response (GSR) indicates the psychophysiological of emotion, EDG is an emerging signal used in the field of emotion classification aside from Electroencephalography (EEG) and Electrocardiography (ECG). The Empatica E4 wearable device was used in collecting EDG signals and employed as the method in capturing the test subject's physiological signal of their skin activity. This experiment had 10 participants that use a Virtual Reality (VR) headset for viewing video stimuli in 360 degrees while collecting the EDG signals. Python with Support Vector Machine (SVM) was used in processing the 10 subjects' data. This paper aims to compare the accuracy of the SVM experiments with different parameters, different settings based on the data retrieved from the wearable. The emotions were classified into four distinct quadrants with inter-subject classifications yielding an accuracy of 54.3%, and intra-subject classification yielded an accuracy of 57.1% to 99.2%. The presented results show that it is possible to achieve results with higher accuracy when parameter tuning. Hence, promising results were demonstrated for emotion prediction in four quadrants using wearable EDG technology in virtual reality environments. This paper provides two contributions, the use of EDG signals in emotion prediction, and the parameter setting to increase the accuracy for SVM classification.

1. Introduction

Emotion recognition and affective computing have been a significant field of study in the last decade, with increasing numbers of applications with the potential of building a human-machine interface. One of the most important psychophysiological signals is Electrodermography (EDG). EDG refers to the conductivity and the electrical activity of the skin. EDG measures the skin conductance in the unit of microSiemens (μS). Nowadays, researchers can acquire EDG signals from subjects through the use of wearable which is a non-obtrusive device. The EDG sensors are embedded in the wearable, thus easy application to the users during the experiment. However, few works have been published thus far [1]. Stimuli play an important role in increasing the EDG response, this reduces the complexity of the emotion recognition process [2]. Moreover, the use of EDG signals showed promising results [3].
A method to identify the state of the subject was suggested by transforming EDG signal using short-time Fourier transform [4]. The use of stimuli is important to increase the EDG responses of the subject, which reduces the complexity of emotion recognition processes [2]. Other related work found that using audio stimuli shows the promising result when EDG signal is in use [3, 5].

The major limitation this paper aims to investigate is as follows. First, limitation concerning Intra-subject classification, to test emotion classifier for EDG signals. Second, the use of EDG signals is still limited, a great number of researchers use EEG or ECG signals. Third, most published works focus heavily on 2 class emotion classification (arousal/valence) [1]. Section 2 presents the methodology and approaches in the experiment. Section 3 presents the overall results of the classification using Machine Learning. This paper concludes in Section 4.

2. Methodology
In this section, the methods used in the experiment are explained in detail. Virtual Reality (VR) was employed for the arrangement of this experiment, VR was used to present the participants with stimuli of emotional content, participants were presented with 360° videos to evoke their emotional responses. Four quadrants as shown in Figure 1 were chosen as the content to evoke the participant's emotion. In each quadrant, participants were exhibited with four concurrent short videos to give a sustained and high response for the focused emotion. A resting period of 10 seconds with a blank visual was presented towards the completion of each quadrant to allow participants to reset their emotional state to their baseline. This is to prepare the participants for the next quadrant of emotional state.

![Figure 1: Russell’s emotion model based on valence and arousal](image)

- **High Arousal/Positive Valence (HA/PV).** The positive emotions associated with this class include excited and happy.
- **Low Arousal/Positive Valence (LA/PV).** The positive emotions associated in this class include emotions such as calm, relaxed, and pleased.
- **High Arousal/Negative Valence (HA/NV).** The emotions associated in this class include emotions such as distress, fear and anger.
- **Low Arousal/Negative Valence (LA/NV).** The negative emotions associated with this class include depressed and sad.

Overall, for this experiment, 16 videos were compiled and merged and presented to the participants over the four emotional quadrants. Figure 2 presents the experiment flow of the videos the
participants are presented with. A time span of 6 minutes and 5 seconds of the merged videos were presented to the participants. For the baseline starting state, the signals were acquired for 5 seconds, and 80 seconds for each quadrant followed with a 10 seconds rest to revert the subject to the baseline.

![Figure 2: Flow of 360° Video Presentation in Eliciting Emotional Response from Subject](image)

3. Subjects, Wearable, and Settings
This section discussed the subjects, wearable, and settings during these experiments. This experiment has a total of 10 subjects (9 males) that participated, with age ranging from 20-28 years old, these individuals are working or studying. The side effect potential was informed and briefed to all subjects before the experiment started. Side effects including motion sickness, headache, nausea, and dizziness, may occur during the use of Virtual Reality (VR), it is commonly associated with the stimuli of the presentation device.

The following shows the methodology flow during the experiment, including equipment, signal retrieved, and the classification process.

![Figure 3: Methodology of the experiment](image)

Figure 3 presents the methodology flow of the experiment, starting with the equipment used, the HTC Vive VR headset for the subject to view the 360-degree videos, Empatica E4 which is the device used to collect the subject EDG data. Next is Data Collection, EDG signals data from 10 subjects were
collected. Python was used as the classification tool, with SVM as the classifier with the tuned parameter for each experiment. Then the two experimental results were compared.

To acquire the Electrodermography (EDG) signals, the Empatica E4 wearable wristband was used. It is a medical-grade wearable device used for acquiring psychophysiological data. The device itself is non-invasive and offers unobtrusive monitoring. The EDG sensor measures the fluctuating changes constantly in certain electrical properties of the skin. EDG reading is influenced by the length of the recording, material of the electrodes, the position of the electrodes on the body, and the environmental conditions during the recording. The attachment of the wearable is placed on the left or right wrist of the subject, after strapping the wearable on the participant's wrist, the VR headset along with the earphones are then attached, the subjects are then in a seating state. During the experiment, the 360° and the recording of the EDG signals were captured simultaneously via a smartphone application.

![Figure 4: The Empatica E4 Wearable](image)

![Figure 5: Attached VR Headset on the subject](image)

Figure 4 presents the wearable device Empatica E4 on the wrist of the subject, while Figure 5 shows the VR headset attached to the subject head. The VR headset is used to present the stimuli of 360 videos to the subject to evoke their emotional responses.

![Figure 6: EDG Signals being recorded with the Empatica E4 Realtime application](image)
Figure 6 shows the Empatica E4 Realtime application used to record the participant's EDG signals during the experiment, it offers real-time monitoring of the EDG signals being captured. Axis X shows the time elapsed, while Axis Y shows the constant fluctuation of the skin activity.

After the EDG signals have been obtained, the subject's data are then uploaded to the cloud via the Empatica E4 Realtime Application which is available for Android and iOS devices. The Comma Separated Value (CSV) file can then be downloaded from the web through the E4 Connect website to be processed.

4. Results and Discussion
In this section, the results of the Electrodermography (EDG) data Intra-subject and Inter-Subject classification were discussed. Two experiments were conducted with 10 subjects in obtaining the EDG signals with the use of wearable and Virtual Reality (VR) headset to present subjects with 360° videos. All of the experiments classified using machine learning with the Support Vector Machine (SVM) classifier to find each of the emotion quadrant’s accuracy. The first experiment parameter was tuned to (0.001, 0.01, 0.1, 1), while the second experiment parameter was tuned to (100, 1000, 2000, 3000). A table comparing all of the experiment is presented in table 1.

4.1 Classification Results for Inter-Subject and Intra-Subject using SVM with Tuning Support
The two experiment results for the emotion classification in four-quadrants using EDG signals with 360° video as the stimuli are as follows. Intra-subject refers to the classification of the subject as an individual while Inter-subject classification refers to the overall subject classification.

![Figure 7: Intra-Subject and Inter-Subject Classification Accuracy Result for Experiment 1](image)

The above figure presents experiment 1 result of processing the EDG signal data through machine learning using SVM with the parameter tuned to 0.001, 0.01, 0.1, 1. The results show the Intra-subject classification's highest accuracy yielded was 96.8% from subject 5, while the lowest accuracy yielded was at 57.1% from subject 8. The Inter-subject classification accuracy yielded 43%.
Figure 8: Intra-Subject and Inter-Subject Classification Accuracy Result for Experiment 2

The above figure presents the result of experiment 2. The EDG signal data were processed with machine learning with parameters tuned to 100, 1000, 2000, 3000. The results show the Intra-subject classification highest accuracy at 99.2% from subject 5, while the result of the lowest accuracy at 60.7% from subject 8. The Inter-subject classification accuracy yielded 54.4%.

Next, a table of the two experiment results is compared in the following table including the increase and decrease of accuracy percentage.

Table 1: Comparison of EDG Results for Intra-Subject and Inter-Subject Classification

| Subject | EXP 1* | EXP 2** | Increase/Decrease*** |
|---------|--------|---------|-----------------------|
| 1       | 70.0%  | 68.0%   | -2.9%                 |
| 2       | 94.1%  | 94.1%   | 0%                    |
| 3       | 61.0%  | 64.0%   | +4.9%                 |
| 4       | 80.0%  | 98.0%   | +22.5%                |
| 5       | 96.8%  | 99.2%   | +2.5%                 |
| 6       | 76.6%  | 84.0%   | +9.7%                 |
| 7       | 63.0%  | 70.0%   | +11.1%                |
| 8       | 57.1%  | 60.7%   | +6.3%                 |
| 9       | 83.6%  | 84.4%   | +0.9%                 |
| 10      | 75.8%  | 64.5%   | -14.9%                |
| Inter   | 43.0%  | 54.4%   | +26.5%                |

* [0.001,0.01,0.1,1.1]
** [100,1000,2000,3000]
*** Increase/Decrease in percentage between experiment 1 and 2

Table 1 shows the classification results of 2 experiments with 10 Intra-subject classifications and Inter-subject. Experiment 1 Intra-subject classification's highest accuracy is 96.8% from subject 5 while its lowest is at 57.1% from subject 8, with Inter-subject classification at 43. For experiment 2, the highest accuracy for intra-subject classification is 99.2% from subject 5 while its lowest accuracy is 60.7% from subject 8, with Inter-subject classification performed at 54.4%.
Increasing the parameter from Experiment 1 [0.001,0.01,0.1,1] to Experiment 2 [100,1000,2000,3000], there were notable changes in the accuracies. Subject 4 increased the most with 22.5%, Subject 2 had no changes, subject 10 had a decreased accuracy of 14.9%, with Inter-subject had increased accuracy by 26.5%.

By experimenting with different parameters, different results were achieved. A higher value parameter achieved significantly better accuracy when compared to the lower value parameter.

Conclusions

These are the results for Inter-subject classification with Electrodermography (EDG) signals for emotion classification using machine learning, overall, experiment 2 performed the best with the parameter tuned to 100,1000,2000,3000, yielding an accuracy of 99.2% for intra-subject classification. Experiment 2 performed better than experiment 1. Inter-subject classification performed the best at experiment 2 with 54.4% when compared to experiment 1 at 43%. This result shows that experiment 2 parameter tuning is better at Inter-subject classification. Overall, for intra-subject classification, subject 5 performed the best accuracy with 99.2% from experiment 2, while subject 8 yielded the lowest accuracy with 57.1% from experiment 1. Furthermore, an observation of the result shows that female subjects had less accuracy when compared to male subjects. This suggests the possibility of conducting further investigation to improve the classification results of female subjects. For future work, first, more testing on human subjects is required to retrieve more data to achieve 100% accuracy, second, to use or combine other signals such as Electrocardiography (ECG) signals, third is to test other classifiers including K-Nearest Neighbor (KNN) and Random Forest.

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