Exploring Standalone Electrodermography for Multiclass VR Emotion Prediction using KNN

A F Bulagang¹, J Mountstephens² and J Teo³*

¹Graduate Researcher, Evolutionary Computing Laboratory, Faculty of Computing and Informatics, Universiti Malaysia Sabah, Jalan UMS, 88400, Kota Kinabalu, Sabah, Malaysia
²Senior Lecturer, Faculty of Computing and Informatics, Universiti Malaysia Sabah, Jalan UMS 88400, Kota Kinabalu, Sabah, Malaysia
³Professor, Faculty of Computing and Informatics, Universiti Malaysia Sabah, Jalan UMS, 88400, Kota Kinabalu, Sabah, Malaysia
*Corresponding author: jtwteo@ums.edu.my

Abstract. The use of Electrodermography (EDG) in emotion classification is emerging in recent studies, however, it is still limited when compared to the use of other physiological signals such as Electroencephalography (EEG) and Electrocardiography (ECG). Galvanic Skin Response (GSR) or EDG can be used in studies relating to the psychophysiological of emotion. This paper presents the result of an experiment conducted using EDG as the main signal for emotion classification with the use of K-Nearest Neighbor (KNN) as the classifier. In the experiment, the EDG data is acquired from 10 subjects while Virtual Reality (VR) headset is used to view 360 degrees video. Python is used as the programming language for the emotion classification with KNN as the classifier to classify intra-subject (individual) and inter-subject (overall) data. The main objective of this paper is to present the result of the experiment when using KNN as the classifier rather than using Support Vector Machine (SVM) which is synonymous with machine learning. The data were then classified into four classes of distinct emotion, inter-subject achieved an accuracy of 54%, while intra-subject classifications, two subjects achieved an accuracy of 96.9%. This result shows that KNN can provide good accuracy for emotion classification using machine learning as an alternative to SVM.

1. Introduction

In the last decade, the study of affective computing and emotion recognition have been significant, the potential application for building an interface for human-machine has been increased. Psychophysiological signals such as Electrodermography (EDG) is one of the most important signals in emotion classification. EDG refers to skin electrical activity and conductivity. By measuring the conductivity of the skin through the unit of microSiemens (μS). EDG signals have been acquired through various type of non-obtrusive wearable devices by researchers. The wearable has an embedded EDG sensor that allows capturing the subject data using an application during the experiment. Thus far, few works have been published on the work of EDG [1]. One of the important
parts in increasing the response of EDG is the stimuli, the complexity of the emotion recognition process can be greatly reduced [2]. Furthermore, results from an experiment that uses EDG signals are promising [3]. This paper aims to investigate the following major limitation. First concerning the limitation of intra-subject classification, to test the EDG signal with K-Nearest Neighbor (KNN) classifier. Secondly, the experiment using EDG signals is very limited when compared to the use of electroencephalography (EEG) or electrocardiography (ECG) signals. Thirdly, a heavy focus on two-class emotion classification (arousal/valence) is published in most works. Next, an explanation of the KNN Classifier is discussed in chapter 2, then, the experiment methodology and approaches are presented in section 3. The subjects, wearable, and setup were discussed in section 4. While the classification using the KNN classifier result is presented and discussed in section 5. At the end is the conclusion of this paper.

2. K-Nearest Neighbor (KNN) Classifier
For this experiment, K-Nearest Neighbor (KNN) is used to classify the Electrocardiography (EDG) data collected from subjects. KNN is a classifier that classifies samples that is unlabelled. It is classified by following the similarity of the training data. KNN finds the samples in the training data that is K's closest neighborhood and labels it with the class that appears the most frequent in the neighborhood [4]. In a comparison review between KNN and SVM, it was found that KNN showed a better result than SVM [5].

3. Methodology
This section explains the detail of the methods that were used in the experiment. This experiment uses Virtual Reality (VR) as the main stimuli to evoke emotion from the subject. The subject was presented with emotional stimuli through the use of VR, subjects were able to view the videos in 360° to evoke a response of their emotion. Figure 1 shows the four quadrants that were chosen to evoke the emotion of the participants. Four videos were presented concurrently in each quadrant to give the participant a sustained and high response in regards to the emotion-focused. Then, a 10-seconds of rest period was given without any visual stimuli towards the end of every quadrant, this is to restart the subject emotional state to their baseline, this prepares the subject for the next emotional presentation stimuli of the following quadrant.

Figure 1: Valence and arousal based on Russell’s emotion model

Figure 1 presents the valence and arousal emotion model by Russell’s, the explanation for each of the quadrant and description is explained below in Table 1.
Table 1: The state of Valence and Arousal and its description

| State of Valence and Arousal                  | Description                                                                 |
|-----------------------------------------------|-----------------------------------------------------------------------------|
| High Arousal/Positive Valence (HA/PV)         | Positive emotions are included in this class such as happy and excited.      |
| Low Arousal/Positive Valence (LA/PV)          | Emotions in this class include relaxed, calm, and pleased                   |
| High Arousal/Negative Valence (HA/NV)         | Emotions in this class include anger, fear, and distressed                  |
| Low Arousal/Negative Valence (LA/NV)          | Negative emotions are included in this class such as sad and depressed.      |

This experiment consisted of 16 videos that were merged and compiled and then presented to the participants, the videos presented represents four emotion of each quadrant. The flow of the experiment of the videos shown to the participants is presented in Figure 2. The videos spanned 6 minutes and 5 seconds along with the baseline shown at the start of the video. The initial baseline state was recorded for 5 seconds and each quadrant is 80 seconds followed by 10 seconds of rest to restart the baseline of the subject.

![Figure 2: 360° Video Presentation flow to Evoke Subject Emotional Response](image)

4. Subjects, Wearable, and Setup
The subjects, wearable, and setup during the experiments are discussed in this section. A total of 10 participants were involved in this experiment, consisting of 9 males and 1 female who volunteered. The age range of the subjects is 20-28 years old, who are working or studying. Before starting the experiment, the subjects were briefed about the experiment as well as informing them about the potential side effect they might experience through the experiment that includes motion sickness, nausea, dizziness, and headache. Virtual Reality (VR) is known to have these side effects on users. VR is used as the stimuli that the subjects wear during the experiment to evoke their emotion for each of the quadrants.

The following shows the flow of the methodology during the experiment that includes equipment, signal acquired, and the process of classification.
Figure 3: Methodology of the experiment

Figure 3 presents the methodology flow of the experiment. HTC Vive VR headset with 360 videos is used for the subject to view, while the Empatica E4 wearable device was used to acquire the subject EDG data. Next is Data Collection, a total of 10 subjects EDG signal data were collected. Then the data is pre-processed before the classification with python begins. Python is then used as the tool to classify the EDG data with KNN classifier for intra-subject (individual) classification and inter-subject (overall) classification.

The wearable Empatica E4 is used to capture the Electrodermography (EDG) signals from the subjects, it is a medical-grade wearable used for acquiring physiological data. It is used for unobtrusive monitoring that is non-invasive. The EDG detects the changes in skin activity through skin electrical properties. The reading of EDG is highly influenced by the recording length, electrodes material, conditions of the environment during recording, and electrodes position on the body. For this experiment, the wearable is attached to the right-hand wrist of the subject, after the wearable is attached, the VR headset and earphone is then attached to the subjects head and ears. The subject is then placed in a seated position. A smartphone application is used during the experiment to record the EDG signals while the subject is viewing the 360° videos.

Figure 5: The Empatica E4 Wearable

Figure 4: The VR Headset attached to the subject
Figure 6: Empatica E4 Realtime application used to record EDG Signals

Figure 4 shows the VR Headset attached to the subject’s head while viewing the 360° videos. Figure 5 shows the Empatica E4 wearable attached on the subject wrist. Figure 6 shows the application for Empatica E4 used in acquiring the subjects EDG signals throughout the experiment. The application provides feed for real-time monitoring of the EDG signal being acquired. The X-Axis shows the elapsed time, while the Y-Axis shows the skin activity constant changes.

After obtaining the EDG signals from the experiment, the data is then uploaded to the cloud using the Empatica E4 Realtime Application. The data can then be downloaded in Comma Separated Value (CSV) from the website to be processed.

5. Results and Discussion
This section presents and discusses the result of this experiment of using Electrodermography (EDG) data for emotion classification for Intra-subject and Inter-subject using K-Nearest Neighbor (KNN) Classifier. The experiment was conducted with 10 subjects EDG data collected using a wearable while wearing a Virtual Reality (VR) headset. The EDG data collected is based on the skin activity of the subject while they were viewing the 360° videos.

5.1 Intra-subject and Inter-Subject Classification using KNN Classifiers
The following figure shows the result of using EDG data for emotion classification in four quadrants with 360° video stimuli. Intra-subject refers to individual subject classification while Inter-subject refers to the overall subject classification.

Figure 7: Intra-Subject and Inter-Subject Classification Accuracy Result for EDG Data with KNN Classifier.
Figure 7 shows the experiment result of processing EDG data using machine learning with KNN as the classifier. The result shows that for intra-subject classification, the highest accuracy achieved was 96.9% from subject 2 and 5, while the lowest accuracy was at 54.6% from subject 8. For the Inter-subject classification of 10 subjects, the accuracy achieved is 54%. Next, Table 2 summarizes the result from Figure 7.

Table 2: Summary of EDG Results with KNN Classifier for Intra-Subject and Inter-Subject Classification

| KNN  | Subject | Percentage |
|------|---------|------------|
| Highest | 2, 5 | 96.9% |
| Lowest | 8 | 54.6% |
| Average | All | 77.89% |
| >90% | 3 | 94.6%-96.9% |
| >80% | 2 | 82.3%-83% |
| >70% | 2 | 70% |
| >60% | 2 | 65.3% |
| >50% | 1 | 54.6 |
| Inter | All | 54% |

Table 2 shows the summary of Figure 7 results of 10 intra-subject classifications and inter-subject classification. The highest accuracy of EDG data classification with KNN is 96.9% from subject 2 and 5, however, the lowest is 54.6% from subject 8. Overall, the average percentage of 10 subjects is 77.89%. Next, 3 subjects achieved above 90%, then 2 subjects achieved above 80%, 70%, and 60%, while 1 subject achieved more than 50% accuracy. For inter-subject classification, the accuracy is 54%.

Conclusions

These are the results for Intra-subject and Inter-subject classification with Electrodermography (EDG) data with K-Nearest Neighbor (KNN) classifier for emotion classification using machine learning. Overall, by using KNN classifier for emotion classification, 2 subjects achieved high accuracy with 96.9%, while inter-subject classification achieved 54% with 10 subjects. Subject 2 and 5 performed the best, while subject 8 achieved the lowest accuracy. For future work, the next experiment will use the Random Forest classifier to compare the result with Support Vector Machine (SVM) and KNN to see which classifier can yield the best accuracy for intra-subject and inter-subject classification. The second is to combine Electrocardiography (ECG) and EDG signals and classify using SVM, KNN, and Random Forest.

Acknowledgments

This work was supported by the Ministry of Higher Education, Malaysia [ref: FRGS0512-1/2019].
References

[1] Al Machot, F.; Elmachot, A.; Ali, M.; Al Machot, E.; Kyamakya, K. A Deep-Learning Model for Subject-Independent Human Emotion Recognition Using Electrodermal Activity Sensors. Sensors 2019, 19, 1659.

[2] Bradley, M.M.; Lang, P.J. Affective reactions to acoustic stimuli. Psychophysiology 2000, 37, 204–215. [CrossRef]

[3] van der Zwaag, M.D.; Janssen, J.H.; Westerink, J.H. Directing physiology and mood through music: Validation of an affective music player. IEEE Trans. Affect. Comput. 2013, 4, 57–68. [CrossRef]

[4] M. Ali, A. H. Mosa, F. Al Machot, and K. Kyamakya, “Emotion recognition involving physiological and speech signals: A comprehensive review,” in Studies in Systems, Decision and Control, vol. 109, Springer International Publishing, 2018, pp. 287–302.

[5] M. Ali, A. H. Mosa, F. Al Machot, and K. Kyamakya, “A Review of Emotion Recognition Using Physiological and Speech Signals,” Ann. Telecommun. - Ann. Des Télécommunications, vol. 109, no. 3–4, pp. 303–318, 2018, doi: 10.1007/978-3-319-58996-1.

[6] Cosić, K.; Popović, S.; Kukolja, D.; Dropuljić, B.; Ivanec, D.; Tonković, M. Multimodal analysis of startle type responses. Comput. Methods Programs Biomed. 2016, 129, 186–202. [CrossRef] [PubMed]

[7] Greco, A., Marzi, C., Lanata, A., Scilingo, E. P., & Vanello, N. (2019). Combining Electrodermal Activity and Speech Analysis towards a more Accurate Emotion Recognition System. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 229–232. https://doi.org/10.1109/embc.2019.8857745

[8] Shukla, J., Barreda-Angeles, M., Oliver, J., Nandi, G. C., & Puig, D. (2019). Feature Extraction and Selection for Emotion Recognition from Electrodermal Activity. IEEE Transactions on Affective Computing, (April). https://doi.org/10.1109/TAFFC.2019.2901673

[9] Liu, Y., & Du, S. (2018). Psychological stress level detection based on electrodermal activity. Behavioural Brain Research, 341(December 2017), 50–53. https://doi.org/10.1016/j.bbr.2017.12.021

[10] Ooi, J. S. K., Ahmad, S. A., Chong, Y. Z., Ali, S. H. M., Ai, G., & Wagatsuma, H. (2016). Driver emotion recognition framework based on electrodermal activity measurements during simulated driving conditions. IECBES 2016 - IEEE-EMBS Conference on Biomedical Engineering and Sciences, 365–369. https://doi.org/10.1109/IECBES.2016.7843475

[11] Kwon, J., Kim, D. H., Park, W., & Kim, L. (2016). A wearable device for emotional recognition using facial expression and physiological response. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2016 Octob, 5765–5768. https://doi.org/10.1109/EMBC.2016.7592037