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Identifying the Optimal Location of Facial EMG for Emotion Detection Using Logistic Regression

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Abstract. In this study, we analyzed the utility of electromyogram (EMG) signals recorded from the zygomaticus major (zEMG), the trapezius (tEMG), and the corrugator supercilii (cEMG) for emotion detection. We computed eleven-time domain features from the EMG signals to classify the emotions such as amusing, boring, relaxing, and scary. The features were fed to the logistic regression, support vector machine, and multilayer perceptron classifiers, and model performance was evaluated. We achieved an average 10-fold cross-validation classification accuracy of 67.29%. 67.92% and 64.58% by LR using the features extracted from the EMG signals recorded from the zEMG, tEMG, and cEMG, respectively. The classification accuracy improved to 70.6% while combining features from the zEMG andcEMG for the LR model. However, the performance dropped while including the features of EMG from all three locations. Our study shows the importance of utilizing the zEMG and cEMG combination for emotion recognition.

Keywords. Emotion detection, facial electromyography, feature extraction, machine learning.

1. Introduction

Emotional state analysis and classification may be a potential approach for distinguishing between various disorders [1]. Emotions can be detected based on facial expressionsusing

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facial images and video processing [2]. However, this method has some drawbacks, such as sensor alignment and light conditions, which can affect the accuracy of emotion detection. Additionally, facial expressions can be controlled to some extent by humans, and this difficulty is also observed in some health conditions like autism or bipolar disorder [1]. To overcome these limitations, researchers have turned to electromyography (EMG) signals for emotion detection. EMG signals are related to the natural muscle movement of the self-directed nervous system. When the brain signal is activated, it causes electrical potential in muscles, which usually occurs in facial expression. There- fore, EMG signals can be a valuable tool for emotion detection [3]. In this study, the muscle activity of three different muscles, namely Zygomaticus major (zEMG), Corrugator supercilii (cEMG), and Trapezius (tEMG), was analyzed for emotion detection. These muscles were chosen because emotional states are reflected on the face on muscle activity at the corrugator, the orbicularis oculi, the zygomatic, and the frontalis regions. Out of these muscle activities, the corrugator and zygomaticus give more information on facial expression. Additionally, the trapezius muscle can also contribute to emotional state analysis [4]. To identify the optimal muscle location for emotion detection, the time domain features were extracted, and machine learning models such as logistic regression (LR), support vector machine (SVM), and multilayer perceptron (MLP) were used. The results of this study can be used to develop more accurate and reliable tools for emotion detection, which can be beneficial in various fields, including healthcare, psychology, and entertainment.

2. Methods

The process pipeline followed in this study is depicted in Figure 1.

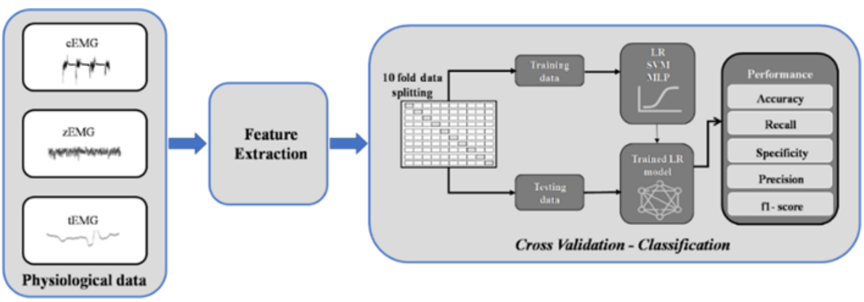

Figure 1. Process pipeline of the study

We considered the EMG signals publicly available in the Continuously Annotated Signals of Emotion (CASE) dataset [5]. EMG signals were recorded from the three different muscle regions such as zygomaticus major (zEMG), corrugator supercilia (cEMG), and trapezius (tEMG). The dataset consists of EMG signals of 30 subjects recorded while stimulating four emotions, namely amusing, boring, relaxing, and scary. We extracted the time domain features such as mean, median, standard deviation, area, maximum value/peak, minimum value/peak, dynamic range, mean of first derivative, mean of second derivative, standard deviation of first derivative, standard deviation of second derivative from each EMG signal. TheLR classifier model was built using the features extracted from individual EMG muscleregions and possible combinations to identify the muscle regions which help in emotion detection. The performance of the classification models was cross-validated using a10-fold stratified method, and metrics such as accuracy, recall, precision, specificity, andf1-score were computed. We compared the performance of LR with SVM and MLP [6]

3. Results and Discussions

Figure 2 shows the performance of LR classifier on emotion classification using features extracted from different EMG muscle regions. It can be noted from the figure that the performance of the LR classifier is high with cEMG, followed by zEMG and tEMG. It indicates that the facial EMG can supply more emotion detection information than the shoulder muscle regions. We achieved high average classification accuracy, specificity, recall, precision, specificity, and f1-score of 67.92%, 25%, 82.22%, 31.91%, and 28.04%, respectively using cEMG and LR. We can observe from the figure that the LR model built using zEMG and cEMG performed better compared to SVM and MLP models. Moreover, classification performance is slightly reduced while building a model with all three EMG signals. It again justifies the role of facial muscles in emotion detection. We achieved the highest classification accuracy, specificity, recall, precision, specificity, and f1-score of 70.62%, 41.25%, 80.42%, 38.02%, and 35.96% respectively using zEMG+cEMG and LR model.

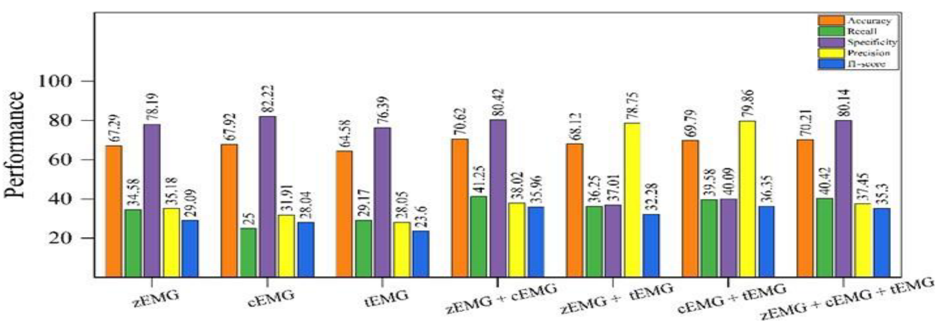

Figure 2. Classification result of LR for zEMG, cEMG, tEMG, zEMG+cEMG, zEMG+tEMG, cEMG+tEMG, zEMG+cEMG+tEMG

Table 1 summarizes the performance of LR, SVM, and MLP on emotion detection using zEMG+cEMG. It can be noted that LR outperforms SVM and MLP classifiers in emotion detection. We found similar results in utilizing other EMG locations using these classification models.

Table 1. Performance of machine learning models on zEMG+cEMG

Machine learning model	Accuracy	Recall	Specificity	Precision	f1-score
LR	70.62	41.25	80.42	38.02	35.96
SVM	67.29	34.58	78.19	29.13	36.50
MLP	70.00	40.00	80.00	39.77	37.90

4. Limitations and Future work

We achieved comparable emotion classification accuracy using time-domain features extracted from zEMG+cEMG and LR models. Further, the classification accuracy can be improved by including process pipelines with more features and other machine learningand deep learning models. In the future, we can include multi-models with other physiological signals in addition to EMG for emotion classification. We can extend this study to develop a wearable device. This study can be extended by adding more features and exploring different classifiers.

5. Conclusions

In this study, we investigated the performance of EMG signals acquired from different muscle regions for emotion detection. We used the time domain features and LR classifier. Our results suggest that the features extracted from zEMG+cEMG and LR models were able to detect the amusing, boring, relaxing, and scary with an average 10-foldcross-validation accuracy of 70.62%. These facial muscles could contribute more information compared to the trapezius muscle region. The proposed study can be a valuable tool for emotion detection and human decision-making.

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