A Fusion of Wavelet-based and Unsupervised Machine Learning Method for Artifacts Removal in Electrodermal Activity Signal

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***Abstract*—The fast tempo of modern society has brought people a series of emotional changes and mental pressures. Therefore, research have emerged to help people pay attention to and regulate their mental health. Physiological signals are used in studies from different fields to monitor and detect emotional change and stress. Electrodermal activity (EDA) is such a physiological signal that can reflect changes in skin conductivity when people's emotions change. The nature of neuromodulation makes such changes not easily controlled by people subjectively so EDA is an ideal emotion and stress monitoring indicator. Especially with the popularity of wearable devices in the market, wearable devices with built-in EDA sensors will be more competitive for the functions that help people regulate their mental health. However, since the EDA sensor usually acquires signals through fingers, palms, or wrists, artifacts will inevitably be generated when users move their hands or arms, and the artifacts will affect the accuracy of emotional change detection. As a result, removing artifacts in EDA signals is a challenging and important topic. In this work, multiple signal processing methods are applied to realize the objective of removing artifacts in the EDA signals from the AMIGOS dataset. The results show that the proposed method is promising and has the potential to be utilized in real-time EDA signal processing and emotional change detection applications.**

***Index Terms*—EDA, motion artifacts, artifact removal, machine learning**

I. Introduction

With the acceleration of the pace of life and work, the increase of competition pressure, the expansion of social experience, and the change of way of thinking in modern society, there may be mental stress in work, study, life, interpersonal relationships, and self-awareness. Especially today, when science and technology are highly developed, people focus on physical health but easily ignore mental health. There is an inherent correlation between human psychological activities and the physical functions of the human body [1]. An excellent and steady emotional state can make the physical function in the best condition. On the contrary, it will negatively impact physical functions, affecting work and life and leading to various diseases. Although mental health is a subjective experience of the individual, emotional state changes and stress can be measured with physiological signals [2], such as Electrodermal Activity (EDA), Electrocardiography (ECG), and Electroencephalography (EEG). Among these physiological signals, EDA is widely used in research for stress or emotion recognition.

Skin can reflect emotional changes due to psychological changes or external stimuli through changes in skin resistance [3]. EDA is one of the most sensitive emotional feedback, also known as Galvanic Skin Response (GSR). EDA arises from the autonomous activation of the skin's sweat glands, triggered by emotional stimuli. When there is a change in people's moods, EDA signals show patterns that can be statistically quantified by observation. With EDA, it is possible to test mental state under the control of unconscious behavior, that is, without subjective cognitive state control. In this case, EDA is a hallmark of emotional arousal, which provides an understanding of an event's impact on mental activity.

With the development of technology, wearable devices such as fitness trackers and smartwatches are gradually becoming essential lifestyle device that helps people track their activity level and basic health parameters. A variety of physiological signal sensors are implemented in wearable devices. For example, Photoplethysmography (PPG) sensors detect heartbeats per minute, SpO2 sensors measure the oxygen level in the blood, and ECG sensors detect the tiny electrical pulses that happen with each heartbeat. Recently, EDA sensors are also starting to be added to wearable devices due to the increasing emphasis on mental health, such as the Fitbit Sense and Charge 5 [4] and the Empatica E4 [5]. However, due to users' body movements, sensors in the wearable device will be mixed with noises during the signal acquisition process. Especially the motion artifact (MA), caused by the change in the gap between the skin and the wearable device or the device's tiny displacement, results in inaccuracy signal values. Inaccuracy signals will cause errors in data analysis, leading to poor generalization ability of emotion or stress recognition models. Consequently, it is crucial to understand the causes of motion artifacts and select effective methods to recognize and eliminate them in specific applications.

To address these challenges, this paper proposes a fusion of wavelet-based and unsupervised machine learning methods for motion artifact removal in EDA signals collected from wearable devices. The rest of this paper is as follows: Section II reviews the recent related works; Section III introduces the features of the EDA signal; Section IV presents the methodologies used in this study, and Section V presents the results and discussions of the experiment; Section VI concludes this study.

II. Related Works

In recent years, numerous studies on using EDA to detect emotional changes have been proposed, and different stimuli and emotion classification methods are applied to these studies. In [6], they chose acoustic stimuli from the International Affective Digitized Sound System database [7] to arouse the participants' emotions and used K-nearest neighbors algorithm (KNN) to perform the classification. Also using KNN as the classifier, in [8], they conducted arousal detection experiments with musical stimuli. In [9], they modified parts of 25 classical music pieces to different levels of unexpected chords as stimuli. They investigated the correlation between the designed music and the changes in physiological signals (EDA, Heart rate, and Electroencephalogram). In [10], they extracted wavelet high-frequency feature subset from the EDA signals collected when the participants were watching music videos and proved that this feature subset could offer higher classification accuracy than time domain features.

For emotion recognition and stress detection, the common classifiers are machine learning or deep learning models. In [11], the authors used six machine learning methods to assess the stress detection accuracy based on physiological signals from two datasets, WESAD (Wearable Stress and Affect Detection) [12] and the CLAS (Cognitive Load, Affect and Stress Database) [13], while the Stacking Ensemble Learning (SEL) has the best accuracy of 86.4% based on the EDA signals in WESAD. Machine learning models for stress detection were built and evaluated with the datasets VerBIO [14] and WESAD as well in [15]. In [16], features in the time domain, frequency domain, time-frequency domain, and the Mel-Frequency Cepstral Coefficients (MFCC) from the EDA signals in the AMIGOS dataset [17] were used for emotion recognition, and a Support Vector Machine (SVM) was adopted for the classification task. In [18], [19], Convolutional Neural Network (CNN) and Multiscale Deep Convolutional Neural Network (DCNN) were used for emotion recognition and achieved an accuracy of 72.00% and 75.00, 69.80% and 79.10% for valence and arousal, respectively.

However, since motion artifacts are inevitable during the experiments, further research for artifact detection and removal methods is necessary, or the classification accuracy will be negatively affected by the abnormal samples in the EDA signals. In [20], they used curve fitting and sparse recovery methods to recognize and remove artifacts in EDA signals. In [21], they created an EDA dataset that has labeled noisy and clean data. Several machine learning methods were used to detect the noisy data and the Gradboost model obtained the optimal accuracy of 93.87%. With the same dataset, they proposed another novel deep learning method, deep convolutional autoencoder (DCAE), to perform the motion artifacts removal in [22]. In [23], 44 participants experienced multiple tasks that could induce stress in a virtual working environment. A Recurrent Neural Network (RNN) model applied to raw EDA signal was the optimal model to recognize the motion artifacts, and either the Continuous Decomposition Analysis (CDA) or cvxEDA can be used to tackle the following artifact correction problem. Unlike collecting data in a controlled laboratory environment, they collected the EDA signals from patients in the real operating room during surgery in [24]. The crucial steps in the pipeline are using unsupervised machine learning methods and choosing an appropriate threshold to determine the artifacts in the EDA signals and correcting the EDA artifacts by interpolating gaps.

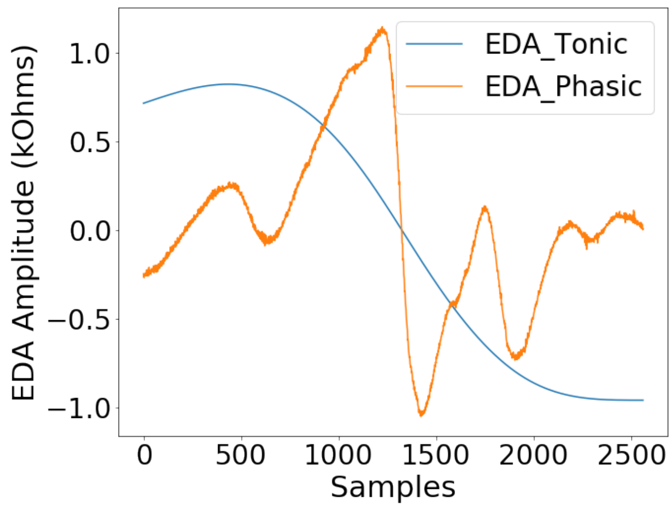

Fig. 1: The tonic and phasic components in a sample period of EDA signal.

III. Electrodermal Activity

Skin is the primary interface between organs and the environment. Along with other organs, it is responsible for bodily processes such as the immune system, thermal regulation, and sensory movement. Skin is also a sensory organ. It contains an extensive network of nerve cells and transmits environmental changes based on temperature, pressure, and pain. Human bodies have about three million sweat glands. Sweat gland distribution varies significantly throughout the body, on the forehead and cheeks, palms and fingers, and feet. When sweat glands are triggered to become more active, they secrete water into the skin surface through the pores. By changing the positive and negative balance of ions in the exudate, electrical currents flow more efficiently, resulting in measurable changes in skin conductance. This change in skin conductance is referred to as Electrodermal Activity. Skin conductance is regulated solely by autonomic sympathetic activity to drive physical, cognitive, and emotional states as well as entirely subconscious cognitive levels.

EDA mainly consists of slowly changing tonic and rapidly changing phasic components [25], shown in Fig. 1. The tonic component is the slow changes in the EDA signal (from tens of seconds to minutes). In the EDA signal, the DC component is often considered the background level of activity where fast EDA responses appear. Baseline levels of the slow component vary widely between individuals, typically between 2 μS and

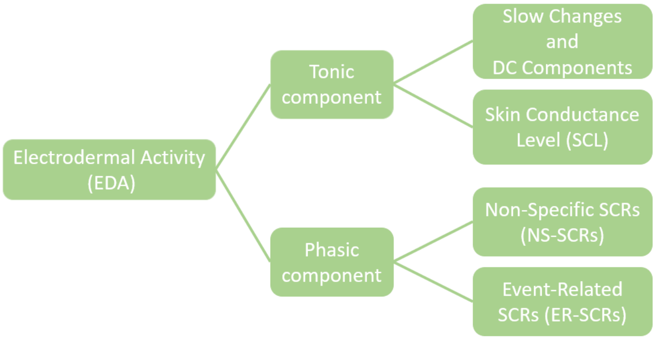

Fig. 2: The components of EDA signals.

20 μS. It can also vary within the same body over a long period, depending on different environmental factors and skin conditions. The most common measurement of the tonic component is the skin conductance level (SCL). Several studies suggest that changes in SCL may be related to general changes in emotional arousal, such as general emotional state and stress levels. Since the SCL changes slowly, the measurement interval must be extended from tens of seconds to minutes. A summary of the EDA components is shown in Fig. 2.

The phasic component is the relatively rapid changes in the EDA signal, known as the skin conductance response (SCR). SCRs are rapid fluctuations or spikes that can be observed in the EDA signal. Responses to specific events, such as visual stimuli or unexpected questions, generate SCRs, which are event-related SCRs (ER-SCRs). ER-SCR is the most commonly used measure used in research to correlate changes in emotional arousal to specific stimuli. ER-SCR usually will start 1 to 5 seconds after the event and last for several seconds due to the lag in skin conductance responses. A good stimulus design that allows sufficient time between stimuli is essential to avoid uncertainty about which stimuli cause a certain ER-SCR. SCR occurs spontaneously as well, unrelated to any specific event, and is called nonspecific SCR (NS-SCR). The frequency of NS-SCR may vary between participants, averaging 1-3 times per minute. NS-SCR is also considered to be part of the main component of the EDA signal.

IV. Methodologies

The pipeline of the proposed system is shown in Fig. 3. Details are introduced as follows.

A. Dataset

In this work, the AMIGOS is used, a dataset for affect, personality, and mood research on individuals and groups. AMIGOS has two experiments in different settings to elicit the participants' emotional changes. Then, the physiological signals, including EEG, ECG, and EDA, were collected from the participants by wearable sensors during the experiments. For collecting signals, 40 participants watched 16 short videos individually in the first experiment, and some participants watched 4 long videos by individual or groups in the second experiment. Moreover, both experiments used cameras to record frontal, full-body, and depth video. Emotive EPOC Neuroheadset was used to collect EEG signals (14-channel, 128Hz, and 14-bit resolution), and the Shimmer $2R^4$ platform was used to record ECG (256Hz and 12-bit resolution) and EDA (128Hz and 12-bit resolution) signals. The AMIGOS dataset offers opportunities for researchers to study personality, mood, and emotional responses to individual or group activities and different stimuli based on either unimodal or multimodal physiological signals. In Fig. 4 the emotion distribution of the AMIGOS dataset is illustrated. The four quadrants refer to High-Arousal High-Valence (HAHV), Low-Arousal High-Valence (LAHV), High-Arousal Low-Valence (HALV), and Low-Arousal Low-Valence (LALV). This study will evaluate the proposed methods based on a binary classification for arousal and non-arousal state.

B. Artifacts Detection

The unsupervised algorithms are used for anomaly detection, where it is assumed that the training data consists of mostly clean data.

1) K-Nearest Neighbor (KNN): The KNN algorithm is a basic classification and regression method. The principle of the KNN algorithm is that if most of the k nearest neighbors of a sample in the feature space belong to a certain category, the sample also belongs to this category and has the characteristics of this category. This method only determines the sample category to be classified according to one or several samples in the nearest neighbor. The three essential elements of the KNN model are distance, choice of K value, and classification decision rules.

2) One-Class Support Vector Machine (OCSVM): OCSVM can be used for outlier detection. Constructing the hyperplane between the origin and the single-class training data can determine whether the test sample is similar to the single-class training data. If the test sample is similar to the single-class training data, it can be classified as a similar sample, denoted as 1. If the test sample is not similar to the single-class training set data, it is denoted as -1. Since it can be constructed through a hyperplane, it can be found that the sample to be predicted is "similar" to the training set data, and then the model can be used for outlier detection.

The artifact detection training is based on a 5-second time window, as the motion that causes the artifact does not last long. Typically, the samples do not have smooth rising and recovering phases. The abnormal segments will be marked as outliers.

C. Artifacts Correction

Discrete Wavelet Transform (DWT) is adopted for artifact correction in this study. The coefficients of a DWT with the Haar wavelet applied to the skin conductance at 3 different time scales: 4 Hz, 2 Hz, and 1 Hz. Wavelet transforms are able to capture both frequency and time information, and the Haar wavelet is excellent at detecting sudden changes in signals, which frequently occur during motion artifacts. The segments with outliers which are detected in the previous stage will be

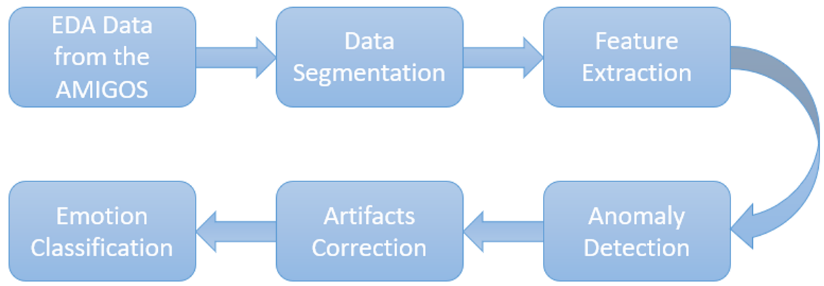

Fig. 3: The pipeline for motion artifact detection system proposed in this study.

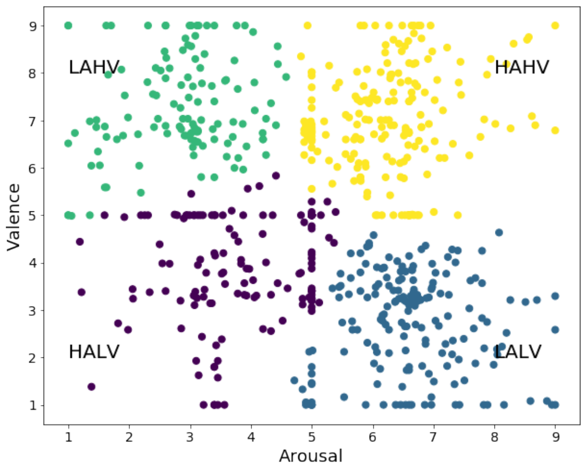

Fig. 4: The distribution of emotional states in the AMIGOS in four quadrants.

corrected with DWT. The segments are combined with their previous 10-second segment and post 10-second segment, if the segments are not marked outliers, so that

D. Emotion Classification

1) Convolutional Network (CNN): With the growing demand for data analysis, traditional machine learning models cannot meet large-scale or complex data sets, such as images and speech. The emergence and development of CNN have solved such problems. A complete CNN can be constructed by stacking Input Layers, Convolutional Layers, ReLU Layers, Pooling Layers, and Fully Connected Layers.

2) Long Short Term Memory Network (LSTM): LSTM is an improved Recurrent Neural Network (RNN) model that can solve the long-distance dependencies problem. In deep learning (especially RNN), the "long-term dependence" problem is ubiquitous. The long-term dependence is that after the neural network nodes have undergone many stages of computation, the features of the last relatively long time slice have been covered. LSTM can solve the long-term dependencies problem of RNN since LSTM introduces a gate mechanism to control the circulation and loss of features.

3) Multilayer Perceptron (MLP): MLP is a feedforward neural network. When there are few hidden layers, a gradient descent learning algorithm is used to learn the weight parameters of the neural network. A given problem determines the number of neurons in the input and output layers. Therefore, the MLP structure design only needs to consider the two hyperparameters of how many hidden layers there are and how many neurons each hidden layer has.

V. Results and Discussions

Table I shows the results of using KNN and OCSVM as MA detectors, followed by classification with CNN, LSTM, and MLP, respectively. All classifications used the Leave-one-subject-out (LOSO) cross-validation. From the results, we can notice that OCSVM is more efficient for MA detection than KNN, regardless of which model is used for the next emotion classification step. The reason that OCSVM is superior in this study can be that OCSVM is not a strict outlier detection but a novelty detection method and the model may match these outliers. In one-class classification, only one class' information can be used for training, and other classes are missing. That is, the boundary line that distinguishes two classes is learned from the information of only one class of data. The MA detection in this study conforms to such a one-class classification. In comparison, KNN is not directly used for anomaly detection. It classifies two or more data classes based on the distance between samples. However, in the classification of unbalanced datasets, the defects of KNN are apparent. Due to the influence of sample distribution, it will shift the minority class to the majority class. The distribution of abnormal and normal points in the dataset in this study is typically imbalanced data, resulting in the OCSVM, which is designed for abnormal detection, being more suitable for the demands of this study.

For emotion classification, the results show that CNN offers better performance than LSTM and MLP. When the MA detector is OCSVM, CNN achieved an accuracy of 88.69%. MLP is a lightweight architecture which requires feature selection, either manually or automatically. When MLP directly classifies the input data, the effect is often unsatisfactory since it is usually challenging for an MLP to have adequate classification performance without feature selection in advance. However, the result is often improved when a deeper multi-layer model

AMIGOS DATASET	CNN	LSTM	MLP
Raw EDA in the original dataset	0.8124	0.7928	0.6845
Cleaned EDA in the original dataset	0.8513	0.8117	0.7113
EDA MA Detection with KNN	0.8725	0.8243	0.7287
EDA MA Detection with OCSVM	**0.8869**	0.8497	0.7523

Table I: The accuracy of prediction results with three classifiers based on raw and cleansed EDA signal.

is used since the model is capable of extracting valuable features. The final output layer of an MLP and a deeper model, respectively, is that an MLP directly faces the raw data while the other has important features that the previous layers have processed. Although LSTM is a deep learning model for time-series data, such as EDA signals, the architecture may be complicated for a simple binary classification task. The CNN used in this study has three layers, which is a straightforward structure fitting for the scale and objective of the binary classification problem here.

VI. Conclusion

This study proposed an automatic motion artifact detection and correction method for EDA signals. Two unsupervised algorithms, KNN and OCSVM, are assessed for artifact detection, followed by discrete wavelet transform, which is used for artifact correction. Then three deep learning models, CNN, LSTM, and MLP, are evaluated for emotion classification. The results show that the combination method of OCSVM for MA detection and CNN for emotion classification outweighs the other proposed method in this study. The combination of OCSVM and CNN achieves an accuracy of 88.69%. The limitation of this work is that no ground truth label can be referenced for the MA in this dataset. Consequently, the evaluation of the proposed methods is based on the final emotion classification results. The preliminary results in this study show the potential of using this method for further future research related to motion artifact detection and removal.

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