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Comparative Analysis of Electrodermal Activity Decomposition Methods in Emotion Detection Using Machine Learning

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Abstract. Electrodermal activity (EDA) reflects sympathetic nervous system activity through sweating-related changes in skin conductance. Decomposition analysis is used to deconvolve the EDA into slow and fast varying tonic and phasic activity, respectively. In this study, we used machine learning models to compare the performance of two EDA decomposition algorithms to detect emotions such as amusing, boring, relaxing, and scary. The EDA data considered in this study were obtained from the publicly available Continuously Annotated Signals of Emotion (CASE) dataset. Initially, we pre-processed and deconvolved the EDA data into tonic and phasic components using decomposition methods such as cvxEDA and BayesianEDA. Further, 12 time-domain features were extracted from the phasic component of EDA data. Finally, we applied machine learning algorithms such as logistic regression (LR) and support vector machine (SVM), to evaluate the performance of the decomposition method. Our results imply that the BayesianEDA decomposition method outperforms the cvxEDA. The mean of the first derivative feature discriminated all the considered emotional pairs with high statistical significance ($p<0.05$). SVM was able to detect emotions better than the LR classifier. We achieved a 10-fold average classification accuracy, sensitivity, specificity, precision, and f1-score of 88.2%, 76.25%, 92.08%, 76.16%, and 76.15% respectively, using BayesianEDA and SVM classifiers. The proposed framework can be utilized to detect emotional states for the early diagnosis of psychological conditions.

Keywords. Emotion detection, Electrodermal activity, Deconvolution, Time-domain features, Machine learning.

1. Introduction

Electrodermal activity (EDA) is a physiological measure of changes in the sympathetic system, reflecting emotional and cognitive states. It tracks the changing electrical conductance of the skin due to the activity of sweat glands and is composed of tonic

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and phasic components [1]. The tonic component is a slowly varying or low-frequency signal of EDA. It is influenced by the thermoregulation of the body as well as the surrounding air's humidity and temperature. Additionally, the tonic component includes information on an individual's degree of overall arousal. On the other hand, the phasic component reflects neural stimulation from the sympathetic nervous system and is a fast-varying or high-frequency component of EDA [2]. The performance of emotion detection highly relies on decomposition methods, so it's essential to find a reliable decomposition technique that will improve the human emotion monitoring system. Researchers have proposed a variety of EDA decomposition methods such as non-negative deconvolution, dynamic causal modelling, cubic-spline-based non-negative sparse deconvolution (cvxEDA), compressed sensing, non-negative sparse deconvolution (SparsEDA) [3] and BayesianEDA [4]. The performance of the decomposition methods can be evaluated using feature extraction methods and machine learning algorithms. Time, frequency, and time-frequency domain features calculated from the EDA were used to characterize the emotional states [5]. Linear, non-linear, ensemble, and deep learning-based classifiers were used in the literature for recognizing emotions using EDA signals [6]. In this study, we decomposed the EDA signals using cvxEDA and BayesianEDA methods and calculated the time domain features. The performance of the decomposition methods was evaluated using a statistical significance test and machine learning classifiers such as LR, and SVM.

2. Materials and Methods

The proposed process pipeline followed in this study is shown in Figure 1.

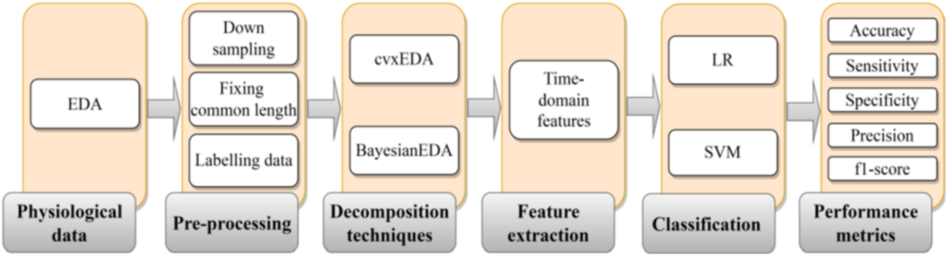

Figure 1. Propose process pipeline

Initially, the EDA signals considered in our study were obtained from the publicly available Continuously Annotated Signals of Emotion (CASE) dataset [7]. The dataset includes recordings of continuously self-annotated physiological signals from 30 participants aged 22 to 37 years (15 male and 15 female). The participants watched eight video clips (mean duration of 158.75 ± 23.67 seconds) to elicit four emotions (amusing, boring, relaxing, and scary, with two videos for each emotion) on a desktop monitor. The video clips were played in different sequences between participants to elicit the appropriate emotions and were recorded in a confined laboratory setting. In the second stage, the EDA signals were down-sampled to 20Hz, and then a common length of 2374 samples was segmented from the end of each EDA signal for the eight video clips (amusing 1 and 2, boring 1 and 2, relaxing 1 and 2, scary 1 and 2) to avoid biasing during the feature extraction process. This optimal length was chosen based on the minimum number of samples available in the dataset for a specific EDA signal (boring1 has a total length of 2374 samples). All EDA signals of the participants recorded during the amusing1 and amusing2 stimuli were grouped under a single class label 'amusing'. The same was applied to the other three emotions, and the corresponding class labels were 'boring', 'relaxing', and 'scary'. In the third stage, the pre-processed EDA was decomposed into tonic and phasic components using the cvxEDA [8] and BayesianEDA [5] methods. A total of 12 time-domain features (input variables) were extracted from the phasic component of each decomposition technique and normalized from 0 to 1 in the fourth stage, as listed in Table 1 [5], [9].

Table 1. Time domain features

Mean (**MN**), Median (**MDN**), Standard deviation (**STD**), Skewness (**SKW**), Kur tosis (**KRT**), Mean of first derivative (**MFD**), Mean of second derivative (**MSD**), Standard deviation of first derivative (**SFD**), Standard deviation of second deriva- tive (**SSD**), Hjorth complexity (**HC**), Hjorth mobility (**HM**), Hjorth activity (**HA**).

We implemented a non-parametric Wilcoxon rank sum test on the features to check their statistical significance. Furthermore, we fed the features to machine learning methods such as LR and SVM [10] to classify categorical emotions such as amusing, boring, relaxing, and scary (output variables). The models were evaluated using 10-fold cross-validation, and the data were balanced during both the training and test phases, ensuring the same number of observations for each class. We performed machine learning using Python 3.6 and the sci-kit learn packages. Finally, we evaluated the performance of the machine learning models using measures such as accuracy, sensitivity, specificity, precision, and f1-score.

3. Results and Discussions

The representative EDA signals of emotions such as amusing, boring, relaxing, and scary for participants and the corresponding phasic component of all emotions using cvxEDA and BayesianEDA were shown in Figure 2(A)-(C).

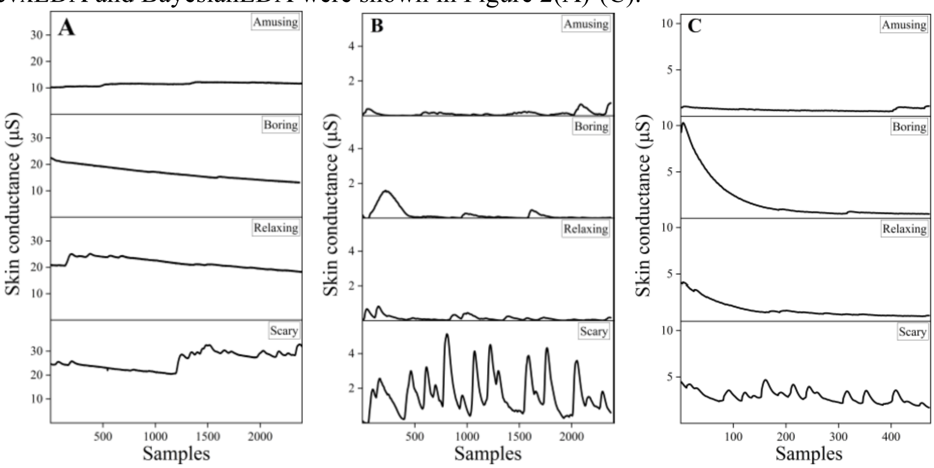

Figure 2. Representative signals of a participant in various emotional states (A) EDA before decomposition, (B) Phasic component deconvolved by cvxEDA, and (C) Phasic component deconvolved by BayesianEDA.

Table 2 shows the statistical significance values of features obtained by the Wilcoxon rank sum test. The six features, such as MN, MDN, STD, SFD, SSD, and HA in cvxEDA were significant for five emotional pairs, and the hypothetical rejection failed on all features for the boring vs. relaxing emotional pair. In contrast, four features such as STD, MFD, MSD, and HA were significant (p<0.05) in BayesianEDA for boring vs. relaxing emotional pairs, and the MFD feature was significant for all emotional pairs. Scary emotion discriminated against the other emotions in most of the features, and it may be due to higher skin conductance caused by more sweat secretion than the other three emotions.

Table 2. Statistical significance of features of cvxEDA and BayesianEDA

	cvxEDA						BayscianEDA					
Feature	AvB	AvR	AvS	BvR	BvS	RvS	AvB	AvR	AvS	BvR	BvS	RvS
MN	*	*	***	0.72	***	***	*	0.54	***	0.13	**	***
MDN	*	*	***	0.98	***	***	0.77	0.58	***	0.82	***	***
STD	**	*	***	0.45	***	***	***	***	***	*	0.20	0.14
SKW	0.35	0.73	0.14	0.78	*	0.10	***	***	***	0.96	***	***
KRT	0.26	0.91	0.36	0.32	0.07	0.45	***	***	0.10	0.77	***	***
MFD	*	0.09	***	0.34	***	***	***	***	***	*	***	*
MSD	0.86	0.60	***	0.30	***	***	**	***	*	***	***	0.21
SFD	*	*	***	0.69	***	***	0.16	0.83	***	0.07	***	***
SSD	*	0.06	***	0.89	***	***	0.64	0.17	***	0.25	***	***
HC	0.54	0.94	*	0.67	*	*	***	***	0.90	0.72	***	***
HM	**	0.05	**	0.16	***	***	***	***	*	0.16	***	***
HA	**	*	***	0.45	***	***	***	***	***	*	0.20	0.14

* $p < 0.05$, ** $p < 0.005$, *** $p < 0.0005$

We fed the features obtained by two decomposition techniques to the classifiers, namely LR and SVM. The average 10-fold cross-validation performance of the two classifiers for four emotions is shown in Figure 3. The results reveal that SVM had greater classification accuracy when employing features derived from the phasic component deconvolved by BayseianEDA. The average classification accuracy, sensitivity, specificity, precision, and f1-score were 88.12%, 76.25%, 92.08%, 76.16%, and 76.15% respectively.

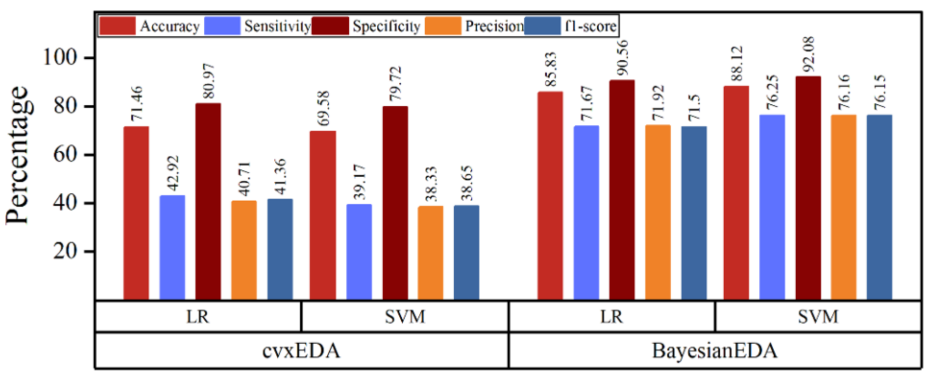

Figure 3. Classification results of LR and SVM classifier

4. Limitations and Future study

In this study, we compared the performance of two decomposition methods using time-domain features and machine-learning algorithms. However, many other decomposition methods were reported in the literature for the deconvolution of EDA data. We evaluated the performance of two decomposition techniques using time-domain features and still need to examine their effectiveness using frequency and time-frequency domain features. We tested with linear classifiers like LR and SVM to detect emotions. In addition, the use of parametric and non-parametric machine learning algorithms, as well as deep learning-based algorithms and unsupervised learning algorithms, may be explored to increase performance. Moreover, by incorporating additional datasets in the future, we can augment our sample size and enhance the statistical power of our analysis, enabling us to test the effectiveness of decomposition techniques with greater accuracy and precision.

5. Conclusion

In this study, the effectiveness of two decomposition methods in emotion detection was analyzed using feature extraction and machine learning. Initially, cvxEDA and Bayesian EDA were used to decompose the pre-processed EDA signals of four emotional states. Each phasic component of the EDA signals was used to extract the time domain features. The effectiveness of decomposition techniques was further validated using statistical tests and machine learning algorithms like LR and SVM classifiers. The MFD feature extracted from the BayesianEDA method discriminated all the considered six emotional pairs with high statistical significance ($p<0.05$). We used a pipeline that included the BayesianEDA phasic component, time domain features, and SVM to achieve an average 10-fold cross-validation accuracy of 88.12%. The proposed framework can be used for the early diagnosis of psychological conditions to identify emotional states.

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