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Feature Selection Framework for XGBoost Based on Electrodermal Activity in Stress Detection

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***Abstract*—Since stress has a strong influence on human's health, it is necessary to automatically detect stress in our daily life. In this paper, we aim to improve the performance and obtain the dominant features in stress detection based on Electrodermal Activity (EDA). Compared to the methods in Wearable Stress and Affect Dataset (WESAD), we propose several enhancements to get higher f1-scores, including less overlapped signal segmentation, more signal processing features, and extreme gradient boosting classification algorithm (XGBoost). Furthermore, we select dominant features according to their importance in classifier and correlation among other features while keeping high performance. Experiment results show that with 9 dominant features in XGBoost, we can achieve 92.38% (+17.87%) and 89.92% (+14.58%) f1-scores compared to WESAD on chest- and wrist-based EDA signal respectively. The features we choose suggest that the magnitude of low frequency and the complexity of high frequency EDA signal contain the most significant information in stress detection.**

***Index Terms*—Stress detection, feature selection, electrodermal activity(EDA), signal processing, extreme gradient boosting**

I. Introduction

There is a strong link between the stress and diseases while pro-longed stress can cause disorders on the psychological and physiological functions [1]. Therefore, automated stress detection is particularly significant, which can enable people to better manage their health. Lots of studies have been proposed to identify stress, such as facial expression or conversation speech [2]-[3]. However, these methods may arise privacy-intrusive problems while human inclines to hide their true feelings. In contrast, physiological measurements collecting from wearable devices cannot be controlled by conscious and have similar properties among different subjects.

Among all the physiological signals, Electrodermal Activity (EDA) is the most sensitive to stress level due to the high correlation between EDA and sympathetic nervous system [4]. Moreover, it can be obtained by several sensors on the skin, e.g. fingers, foot, wrist or chest [5]-[6], which is easily integrated with a smart device. EDA signal consists of two components: a tonic (skin conductance level, SCL) represents a slowly varying baseline conductivity; a phasic (skin conductance response, SCR) shows a fast varying reaction to specific arousing stimulus and can be visible as bursts or peaks.

Although several datasets have applied EDA signal for stress detection [6]-[7], previous experiments commonly regarded stress condition as neutral and stressed state. WESAD [5], a multimodal dataset containing three different affect states (baseline, stressed, amusement), was the newest publicly available benchmark to the best of our knowledge. The baseline and amusement states can be combined to a non-stress class, which was the first time to compare stress with other affect stimuli. The dataset had collected EDA signals from chest and wrist sensor and built a stress detection model with a total of 14 features and 133,000 segments.

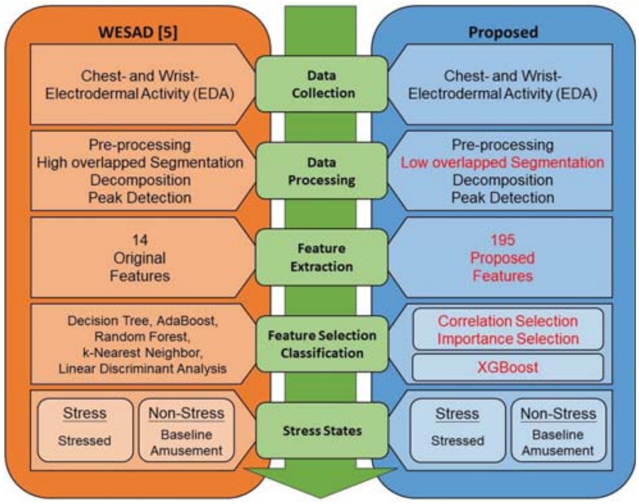

Fig. 1. Overall view of the processing flow. Black text: original methods used in WESAD [5]. Red text: several modifications and methods we proposed.

However, the works based on their achievement still have room for improvement with some modifications, as shown in Fig. 1. In this paper, we first modify the overlapped proportion of segments considering the influence of over-fitting [8]. After then, lots of features in time, frequency, entropy and wavelet domain will be extracted for better analysis on EDA signal [9]. To strengthen the classification algorithms, we introduce XG-Boost [10] as our learning model, which has been supported helpful in emotion recognition [11].

According to the above enhancement, we can improve the performance compared to previous results. However, in order to build an effective and efficient stress detection system, we have to reduce the load of models with the same performance. We propose feature selection methods with feature importance and correlation to acquire the most dominant features related to stress and verify these features with various analysis.

There are two main contributions in our study. 1) We have modified several part of WESAD data processing flow. The

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experiment result suggested that the modified processing flow is more effective for stress detection. 2) We have proposed two feature selection methods considering feature importance and correlation. The experiment results suggest our methods is capable of selecting useful, complementary features. By elimination most of redundant features, our system yield the same higher classification results with less computation effort.

II. Related Work

In recent years, stress detection based on psychological sensors has been a hot research topic. Several studies had worked hard only using EDA signals. Setz *et al.* [12] discriminated stress from cognitive load in a laboratory environment. They extracted 16 features in time domain and analyzed their performance with three common learning algorithms, e.g. linear discriminant analysis (LDA), k-nearest neighbors (KNN), and support vector machine (SVM). Hindra *et al.* [13] conducted experiments also in controlled laboratory settings and used 9 statistical features into different classification models, e.g. k-means, gaussian mixture model (GMM), decision tree (DT), and SVM. Both of the above research investigated simple features with complex models to acquire higher performance, which is lack of other features in different signal representation. Since EDA may be varied from individual or environment, it is necessary to increase the diversity of signal features for a more comprehensive detection system.

According to the feature set in WESAD [5], 14 features are calculated to characterize stress responses in Table I. Besides the basic statistical features of EDA signal (e.g. mean, standard deviation, min, max), they had extracted more features considering tonic and phasic decomposition. However, there are still more signal processing techniques can be applied. Healey *et al.* [6] focused on the information from peak response, Posada-Quintero *et al.* [14] proposed power spectral density analysis in different frequency bands, and Sara *et al.*, [15] suggested that wavelet transforms for EDA have been successfully used in several noise reduction. Furthermore, Visnovcova *et al.* [16] indicated that entropy features would increase obviously during stress tests and decrease during recovery periods.

Considering different signal processing methods, EDA can be extracted into various useful signal features. Due to high dimension of the features, it is necessary to select and verify the most dominant ones for stress detection. Recursive Feature Elimination (RFE) has been widely used for feature selection, which is a recursive method to remove redundant features in each iteration based on a kernel estimator. With RFE, we can find the optimal features based on a specific size to achieve the best result. However, RFE may take more computation costs during training, so we aim to propose more efficient feature selection methods for XGBoost in this paper.

TABLE I
WESAD Feature Extraction [5]

Feature	***Description***
μ_{EDA}, σ_{EDA}	mean and std of the EDA
min_{EDA}, max_{EDA}	min and max of the EDA
∂_{EDA}, $range_{EDA}$	slope and range of the EDA
μ_{tonic}, σ_{tonic}, σ_{phasic}	mean and std of the tonic/phasic
$corr(tonic, time)$	correlation between tonic and time
$number_{phasic}$	number of peaks
$\sum_{phasic}^{amp}$, $\sum_{phasic}^{time}$	sum of phasic startle magnitudes and response duration
$\int_{phasic}$	area under the responses

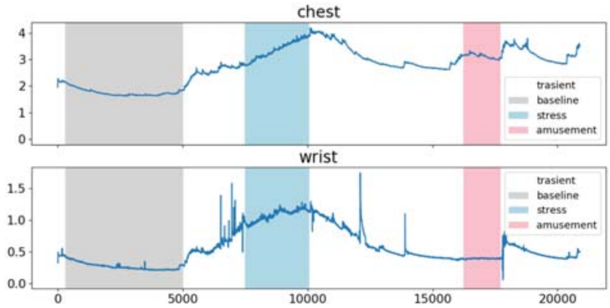

Fig. 2. WESAD experiment setup on EDA signal. Grey: baseline. Blue: stress. Pink: amusement. White: transient.

III. Data Processing

In our research, we first utilise the “chest” and “wrist” EDA raw signal from WESAD. Next, following the classic data processing flow, the signal will be split into segments after undergoing some preprocessing techniques such as downsampling and filtering to remove the artifacts or noise. After then, more signal information will be acquired from EDA decomposition into tonic and phasic components with peak detection. Further details of each step are introduced as below.

A. Dataset

WESAD [5] (WEarable Stress and Affect Dataset) includes data of subjects experiencing both an emotional and a stress stimulus. The data collection was conducted with 15 subjects (3 female) in a laboratory setting. As shown in Fig. 2, each subject experienced three main affect conditions: “baseline” (neutral reading task), “amusement” (watching a set of funny video clips), and “stress” (being exposed to the TSST [17]). The dataset recorded physiological and motion data from both a chest- and a wrist-worn device. The sensor modalities included: electrodermal activity (EDA), electrocardiogram (ECG), blood volume pulse (BVP), electromyogram (EMG), respiration (RESP), skin temperature (TEMP), and 3-axis accelerometer (ACC). In our study, we combine baseline and amusement states as a non-stress class to compare with stress class in a binary classification task. The amusement state was proposed to be a positive stimuli for non-stress class, which is different from only containing baseline state. Among the physiological signals in WESAD, we focus on EDA signal.

B. Pre-processing

As dataset description, EDA raw signal of the chest- and wrist-worn device was recorded at sampling rate 700Hz and 4 Hz respectively. The raw signals may contain lots of noise due to power lines interferences, movements, faulty connections etc. Therefore, we downsample the chest-based EDA signal into 4Hz like wrist signal and apply a 2Hz low-pass filter [9]

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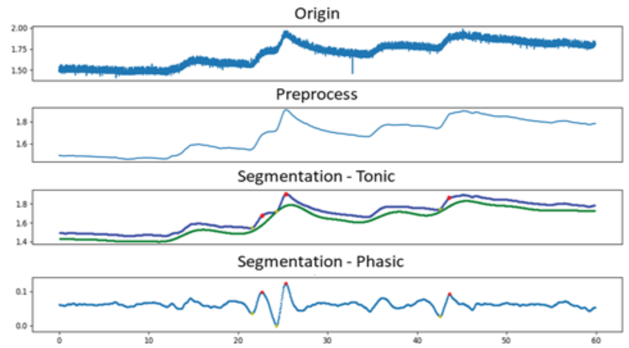

Fig. 3. Data processing flow of EDA signal. Preprocessing and decomposition in the specific segmentation data. Green line: tonic component. Light Blue line: phasic component. Red point: peak. yellow point: onset.

to all EDA signal since physiological plausible changes in the EDA signal are commonly in the low-frequency domain.

C. Segmentation

The data considered in this paper amount to approximately 36 minutes per subject. Among these long time experiments, we implement segmentation to extract different data samples. We segment the samples with 60 seconds window size and overlap the window in 30 seconds, shifting in half proportion of each segments. Total 1041 segments are generated with 15 subjects. Out of these segments, 70.1% belongs to the non-stress class and 29.9% represents the stress condition.

D. Decomposition

Unlike the complicated EDA decomposition method from WESAD, a 0.2 Hz low-pass filter [18] can divide the signal into a smooth and slightly changed tonic components while the residual signal is a high variation phasic component. After separating the tonic and phasic part, we can view these two component as two different decomposition domain and hence additional features can be computed.

E. Peak Detection

A series of rising responses is shown in Fig. 3 along with the marks indicating the red peaks and yellow onsets. The algorithm [6] detects the peaks and onsets by finding the occurrence of the local maximum (peak) between two consecutive local minimum (onset) in phasic component. Detected peaks with an amplitude smaller than a critical threshold of the maximum value are excluded in the segment. By this procedure, we can take into account more information on the level of peak features.

IV. Proposed Feature Selection Framework

There are four proposed methods in our research. First, we reduce the overlapped proportion of segmentation and extract the same features set in WESAD. Second, in order to find more information from the EDA signal, EDA signals from tonic and phasic are analyzed in various signal representation as proposed features, e.g. time, frequency, entropy, and wavelet domain. After then, lots of features in each domain will be fed into a XGBoost machine learning model and output prediction of stress states, which XGBoost is the first attempt to utilize in stress detection to our best knowledge. Finally, we propose an feature selection method using feature importance and correlation in XGBoost to determine the most dominant features for stress detection based on Electrodermal Activity.

A. Proposed Signal Segmentation

The choices of an appropriate window size and overlapped proportion are crucial and depend on several aspects, such as the classification task or the sensor modalities. According to WESAD, segmentation of the preprocessed EDA signals were done using a 60 seconds sliding window with a highly overlapped shift of 0.25 seconds, which would generate 133,000 segments. However, lots of similar data may lead to over-fitting when training a classification model. Therefore, we simply increase the shift size from 0.25 seconds to 30 seconds, half of each segment size for less overlapped segments. Following our proposed segmentation methods, we extract the same feature set in WESAD and use the same classification algorithm to compare the effects of signal segmentation.

B. Proposed Feature Extraction

Different from only fewer features in the previous studies, we aim to analyze the EDA signal with various signal processing methods to enhance the diversity of features. Features contain 36 time domain, 15 frequency domain, 12 entropy domain, and 21 wavelet domain for both tonic and phasic component. Additionally, 13 extra time domain features about peak responses for phasic component are proposed. Total 84 tonic and 97 phasic proposed features are extracted as described in succeeding sections and shown in Table II.

1) Time domain: Previous studies [19] have used 12 traditional time domain features for basic extraction while first difference and second difference of signal with the same method were also calculated, which can provide more information about the variation of EDA signal. In addition to the statistical features of signal, specific features along with peak responses are extracted for stimuli analysis, e.g. amplitudes, intervals, and duration time etc.

2) Frequency domain: To map stress response apart from time domain features, various frequency domain features have been proposed such as power spectrum density (PSD) of EDA signal [14]. Since the power within different frequency bands can extract more detailed features, low and high frequency component are computed in tonic (0-0.1Hz & 0.1-0.2Hz) and phasic (0.2-1Hz & 1-2Hz), respectively. After then, the statistical frequency analysis of the raw signal also provides the information between power and frequency band.

3) Entropy domain: Entropy describes the randomness, uncertainty and messiness of a system and more entropy-domain features have been used in analyzing the physiological signal. First, we analyze the symbolic information entropy, which is coarse graining of time series into symbolic sequences with alphabet to classify the dynamic changes. Next, approximate entropy reflects the probability that two sequences of length

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TABLE II
PROPOSED FEATURE EXTRACTION

Domain	*Type*	*Feature*
Time (T.)(P.)	raw 1^{st} diff. 2^{nd} diff.	mean, standard deviation, skewness, kurtosis mean of $1^{st}/2^{nd}$ diff. mean of absolute $1^{st}/2^{nd}$ diff. mean of negative diff., ratio of negative diff. # local minimum, # local maximum
Time (P.)	peak responses	mean/max/min peaks amplitude from onsets mean/max/min peaks raw value mean/max/min peaks phasic value # peaks, interval of peaks rising time, recovery time
Frequency (T.)(P.)	L.F. H.F.	mean/max/min/ratio/sum of PSD.
Frequency (T.)(P.)	raw	mean/max/min/median of frequency interquartile range of frequency
Entropy (T.)(P.)	raw	approximate entropy symbolic information entropy refined composite multi-scale entropy 1-10
Wavelet (T.)(P.)	L.F. M.F. H.F.	mean, standard deviation, skewness, kurtosis root mean square approximate/information entropy

T.=tonic P.=phasic diff.=difference #=number of
L.F./M.F./H.F.=low/medium/high frequency PSD.=power spectral density

are similar within a tolerance, even if the length of sequence increases by one [16]. After then, we calculate the refined composite multi-scale entropy [11] from scale 1-10 which is an adaptation of multi-scale entropy to resolve the problems of undefined value.

4) Wavelet domain: Wavelet Transforms have been successfully used in several noise reduction application [15] because of their good time-frequency localization. A wavelet transform decomposes a signal into coefficients at multiple scales. In our case, Daubechies-3(db3) mother wavelet is used obtaining for wavelet coefficients [9]. Both tonic and phasic components of EDA signal are decomposed up to level 5. Various statistical and entropy features are extracted from high, medium, and low-frequency wavelet coefficients.

C. Extreme Gradient Boosting (XGBoost)

In addition to the common machine learning algorithms used in WESAD [5], we implement XGBoost as our classification model to predict stress class because of its ability to deal with high-dimensional features or imbalanced data. XGBoost is an ensemble technique based on gradient boosting, consisting of sets of predictors (e.g. decision trees) to become a stronger model. The output of the model can be described in the form:

$$\hat{y_i} = \sum_{k=1}^{K} f_k(x_i), f_k \in F, \quad (1)$$

where K is the total number of predictors, f_k for kth predictor is a function in the functional space F. We use training feature x_i to predict a target variable y_i. In the training, a specific loss function for XGBoost which is optimized at each iteration of gradient boosting is proposed as:

$$L(\theta) = \sum_i l(\hat{y_i}, y_i) + \sum_k \Omega(f_k), \quad (2)$$

where θ is the parameters of the model, l is the training loss function that measures the difference between the prediction $\hat{y_i}$ and the ground truth y_i, respectively. Ω is the additional regularized term penalizing the complexity of the model to avoid over-fitting.

D. Proposed Feature Selection for XGBoost

For XGBoost, good features will be picked as node in the trees and feature size has little influence on the model performance, which we can extract a great amount of features to improve accuracy during training. However, lots of features may reduce the efficiency and increase computational cost for the future application. Therefore, we propose some efficient feature selection method in this section to realize fewer computation by finding the most dominant features.

1) Feature Importance: Since decision tree is typically chosen as the predictor, the importance of each feature can be calculated by counting how many times a feature is used to split the data across all trees, which is helpful for selecting the dominant features in stress detection.

We apply a mechanism to gradually increase the feature size from the most significant features until approaching the same performance with all features. However, similar features may not only reduce their importance due to the less influence on the model performance but also limit our mechanism not to select useful features with different contribution. In order to find dissimilar features along feature importance, we have to obtain the correlation among all features.

2) Feature Correlation: Correlation-based feature selection method has been used widely for machine learning. We reduce the similar features based on Pearson's linear correlation coefficient [20], which is a simple and efficient approach. Among all features, the features with correlation coefficient absolute value higher than 0.9 were grouped and only one selected as representative. After then, we can choose dissimilar important features while keeping model performance and consider these features as the most dominant features in stress detection.

V. EXPERIMENT SETUP AND RESULTS

We conduct two sets of experiments: classification and dominant features analysis. We improve the performance and show the effective enhancements with only few dominant features on the classification results. The dominant features analysis is to verify how the important features we select are useful in stress detection, which we can use an unsupervised classification methods with dominant features to distinguish stress and non-stress easily.

In our experiment, 15 subjects are selected and 1041 samples are generated after data processing. All EDA signals (chest and wrist) are processed into different signal representation, such as time, frequency, entropy and wavelet domain. We normalize the data samples to [-1,1] among different subjects and different features before feeding them into the machine learning model.

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TABLE III
PROPOSED SEGMENTATION PERFORMANCE

	DT	RF	AB	LDA	kNN	XGB
Chest						
WESAD [5]	69.88	73.63	71.97	**74.51**	66.64	NA
our segmentation	85.69	88.78	84.02	88.01	88.18	**89.29**
Wrist						
WESAD [5]	70.95	70.88	**75.34**	69.86	68.30	NA
our segmentation	87.17	87.24	86.70	85.59	**88.91**	87.67

DT=Decision Tree RF=Random Forest AB=AdaBoost XGB=XGBoost
LDA=Linear Discriminant Analysis kNN=k-Nearest Neighbour

TABLE IV
PROPOSED FEATURE EXTRACTION/SELECTION PERFORMANCE

	WESAD [5]	Time	Frequency	Entropy	Wavelet	Fusion
Chest						
Extraction	89.29 (14)	**92.35 (85)**	87.87 (30)	78.87 (24)	91.44 (42)	92.27 (195)
Correlation	89.91 (9)	89.74 (37)	87.45 (15)	74.61 (9)	89.89 (29)	**91.53 (94)**
Importance	90.08 (5)	89.92 (9)	88.53(5)	76.51 (4)	90.31 (10)	**92.38 (9)**
Wrist						
Extraction	87.67 (14)	**89.73 (85)**	84.95 (30)	78.60 (24)	88.42 (42)	89.48 (195)
Correlation	87.02 (9)	88.47 (37)	83.11 (15)	78.36 (9)	**89.62 (29)**	88.94 (94)
Importance	88.40 (5)	88.76 (9)	83.70 (5)	77.95 (4)	**89.92 (10)**	88.78 (9)

Extraction=Extracted features split into time, frequency, entropy, wavelet
Correlation=Dominant features without high correlation
Importance=Dominant features important for XGBoost without high correlation

A. *Classification Results*

We have three goals for the classification experiment, including performance improvement with less overlapped segmentation, various signal processing features, and selection for dominant features. We use XGBoost as our experiment model and apply grid search for model parameters tuning. The classification performance is evaluated in terms of mean F1-score, which is the harmonic mean of precision and recall. We employ leave-one-subject-out as our cross-validation scheme, where the classification models are trained using all data but a previously unseen subject which is used in testing.

1) Proposed Segmentation Performance: The stress detection performance with different segmentation methods compared to WESAD is shown in Table III. The extracted features and the five machine learning algorithms except XGBoost are all applied the same as WESAD. The results show that segmentation can have a great influence on model performance with +15% improvement on the testing set, which we suggest that lots of segments may lead to over-fitting on the similar training samples.

Comparing the performance of the employed algorithms, it is obvious that XGBoost has higher classification scores than other ensemble-based or common-used models on both chest- and wrist-based EDA signals. Therefore, we carry out more experiments on XGBoost to explore its ability for stress detection.

2) Proposed Feature Extraction Performance: As for our enhanced results on XGBoost, we analyze more features on different feature extraction domain as shown in Table IV. Slight improvements compared to WESAD features are +3% and +2% for chest- and wrist-based signal, respectively, which indicate that additional signal processing features of EDA signal are useful for stress detection. Regarding more information on different extraction domains, the results suggest that good features are derived more from time and wavelet domain. These processing features show that the EDA signal wave is

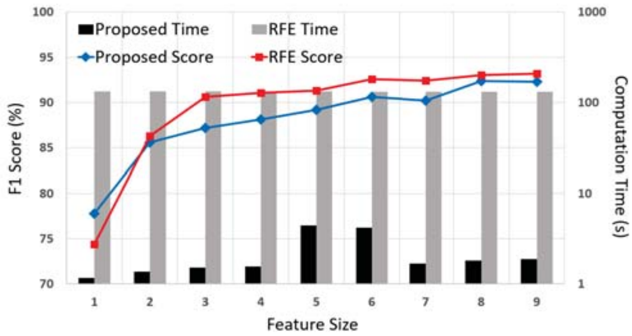

Fig. 4. F1 score and computation time along different feature size for chest-based signal in fusion modality. The performance was compared with different feature selection methods. Blue line: proposed selection f1 score. Red line: RFE f1 score. Black bar: proposed selection computation time. Grey bar: RFE computation time.

sensitive to stress level on time scale and suitable for time-frequency analysis.

3) Proposed Feature Selection Performance: With lots of signal processing features, we proposed two selection methods to select the dominant features based on their importance and correlation. Furthermore, we compare our methods with Recursive Feature Elimination (RFE) considering F1-score and computation time, as shown in Fig. 4. The results suggest our methods with enough feature information can have comparable F1 score to RFE. However, it is considerably less computation time for our methods during training. By removing correlated features and selecting important features for XGBoost, our methods can have more efficient performance.

After feature selection for XGBoost, we can obtain the dominant features with similar high classification scores comparing to all features, as shown in Table IV. Correlation selection can reduce more than half the original features while importance selection can acquire the most dominant features in XGBoost, e.g. features in fusion modality can reduce from 195 features to 9 features. The best performance results on XGBoost are 92.38% and 89.92% using chest- and wrist-based EDA signal respectively. The values indicate that XGBoost is able to identify the stress and non-stress class with the proposed dominant features. Most importantly, our selection methods have the ability to select the features useful for stress detection.

B. *Dominant Feature Analysis*

Dominant features in terms of the feature selection of fusion modality are shown in Table V and the features we propose are highlighted in boldface. The tonic component captures the mean level and the signal range while the phasic component emphasizes the entropy and difference. The result shows that the low frequency magnitude and the high frequency complexity of EDA signal contain the most significant information in stress detection. Moreover, the property of these features indicate the positive correlation with stress level, which suggests that stress can lead to high level and high disorder electrodermal activity.

In addition to the discussion on the information of features, we take the dominant features as a nine-dimensional vector

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TABLE V
DOMINANT FEATURES OF FUSION MODALITY

No.	Dominant features
1	**mean of the tonic**
2	**number of local maximum in 1^{st} difference of phasic**
3	**approximate entropy of high-frequency wavelet of tonic**
4	**information entropy of high frequency wavelet of tonic**
5	**1-2Hz spectral power of phasic**
6	sum of phasic startle magnitudes
7	standard deviation of phasic
8	area under the phasic responses
9	range of the EDA

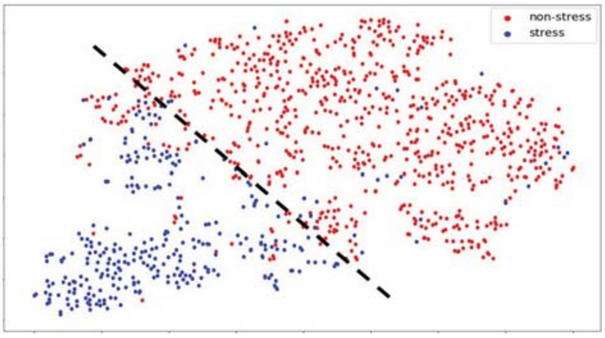

Fig. 5. t-SNE visualization for dominant features based on EDA signal. Red: non-stress. Blue: stress.

among all data segments. These vectors are projected on a two-dimensional space by t-SNE [21], which we can distinguish the data distribution easily, as shown in Fig. 5. The visualization result vindicates the ability of the dominant features to detect the non-stress class and stress class while the non-stress class contains baseline and amusement affect states.

VI. CONCLUSION

In this paper, we propose an enhanced framework for stress detection based on EDA signal. The proposed improvements for higher performance include less overlapped segmentation, more signal processing features, and extreme gradient boosting classifier. Moreover, we obtain the most dominant features related to stress based on the selection of feature importance and correlation. The analysis of dominant feature suggests that the magnitude of low frequency and the complexity of high frequency of EDA signal are useful for stress detection. According to our studies, we can acquire 92.38% and 89.92% f1-scores with 9 dominant features in XGBoost classifier based on chest- and wrist-based EDA signals, which is the state of the art on WESAD using EDA for stress detection.

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