Yedukondala Rao Veeranki*, Nagarajan Ganapathy, and Ramakrishnan Swaminathan

Electrodermal Activity Based Emotion Recognition using Time-Frequency Methods and Machine Learning Algorithms

Abstract: In this work, the feasibility of time-frequency methods, namely short-time Fourier transform, Choi Williams distribution, and smoothed pseudo-Wigner-Ville distribution in the classification of happy and sad emotional states using Electrodermal activity signals have been explored. For this, the annotated happy and sad signals are obtained from an online public database and decomposed into phasic components. The time-frequency analysis has been performed on the phasic components using three different methods. Four statistical features, namely mean, variance, kurtosis, and skewness are extracted from each method. Four classifiers, namely logistic regression, Naive Bayes, random forest, and support vector machine, have been used for the classification. The combination of the smoothed pseudo-Wigner-Ville distribution and random forest yields the highest F-measure of 68.74% for classifying happy and sad emotional states. Thus, it appears that the suggested technique could be helpful in the diagnosis of clinical conditions linked to happy and sad emotional states.

Keywords: Electrodermal activity, emotion recognition, time-frequency analysis, feature extraction, classification

https://doi.org/10.1515/cdbme-2021-2220

1 Introduction

Emotion is a complex state of feeling that impacts decision-making, behaviour, and social interaction [1]. The dichotomous emotions, namely happiness and sadness are frequently experienced by humans [2]. Happiness is associated with increased social behaviour, psychological health, and well-being. Sadness is linked to various mental health disorders, namely anxiety and depression [3, 4]. According to WHO, 264 million individuals suffer from depression across the world [5]. The analysis and recognition of happy and sad emotional states is a promising tool to determine and characterize various neurological disorders.

The circumplex model of affect classifies emotions in two dimensions, namely arousal and valence. Arousal describes the intensity of emotion, whereas valence describes how pleasant or unpleasant emotion is [6]. According to this model, happiness is characterized by high arousal and valence, whereas sadness is characterized by low arousal and valence [7]. Emotions are recognized using different modalities, such as Electrodermal Activity (EDA), electrocardiogram, heart rate, electroencephalogram, blood pressure, and skin temperature. These modalities have attracted more attention since the participants do not easily control them. EDA is one of the most popular psychophysiological signals used for emotion recognition [8].

EDA is a sensitive index that measures variations in electrical characteristics at the skin surface as a result of sweat production [9]. It is considered as one of the potential non-invasive methods for assessing sympathetic control of the autonomic nervous system [9]. The EDA dynamics of exhibit two components: phasic and tonic. The tonic component reflects the slowly varying part of EDA, and the rapid transient events in EDA are reflected by the phasic component. The convex optimization approach (cvxEDA) is a commonly preferred technique for decomposing EDA dynamics [10].

EDA signals are non-stationary and multi-component in nature [8]. Due to this, the use of time-frequency (TF) analysis is inevitable for these signals [8]. The exact multi-component structure can be revealed by choosing the proper TF analysis method. In this study, three TF analysis methods, namely Short-Time Fourier Transform (STFT), Choi Williams Distribution (CWD), and pseudo-Wigner-Ville Distribution (SPWVD), are applied in analysing happy and sad emotional states in EDA.

***Corresponding author: Yedukondala Rao Veeranki:** Indian Institute of Technology Madras, Chennai, India, e-mail: ykraoveeranki@gmail.com
Nagarajan Ganapathy: Peter L. Reichertz Institute for Medical Informatics of TU Braunschweig and Hannover Medical School, Braunschweig, Germany
Ramakrishnan Swaminathan: Indian Institute of Technology Madras, Chennai, India

2 Methods

The proposed study comprised five steps: decomposition, TF analysis, feature extraction, and classification of happy and sad emotional states in EDA signals. Figure 1 depicts the pipeline for the proposed method.

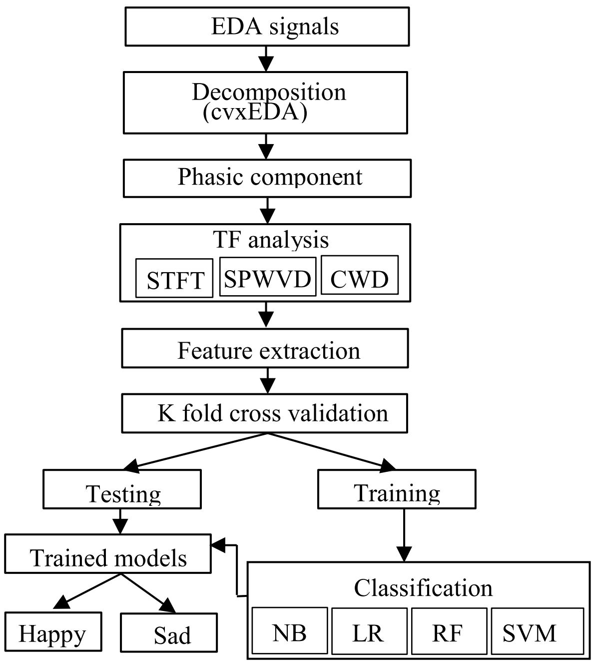

Figure 1: Pipeline of proposed method.

2.1 Database

For this analysis, the EDA signals are collected from the online public DEAP database [11]. The database comprises a wide range of physiological signals, including EDA, which is acquired from 32 subjects while viewing 40 distinct one-minute videos. In this study, the EDA signals associated with one happy and one sad video are considered. The signals are acquired at a sampling rate of 512 Hz and later down sampled to 128 Hz [11].

2.2 Decomposition

The cvxEDA method is used to decompose the EDA obtained from the online DEAP database into phasic components [12]. The method shows better results in the decomposition of EDA at various noise levels [10, 12].

2.3 TF Analysis methods

The phasic component of EDA is analysed by using three TF analysis methods, namely STFT, SPWVD, and CWD.

2.3.1 STFT

STFT analysis is a technique for analysing a signal in the time and frequency domains at the same time. In this technique, the non-stationary signal is converted into several consecutive short-time segments, possibly overlapping, and then the Fourier transform is performed on each segment. The rapid changes in both temporal and spectral events are localized instantaneously using this approach. The mathematical representation of STFT of a signal is defined as:

$$\boldsymbol{STFT(t,f) = \int_{-\infty}^{+\infty} x(\tau) w(\tau - t) e^{-j2\pi f\tau}\, d\tau} \quad (1)$$

Where $x(\tau)$ represents the phasic component of EDA, $w(\tau - t)$ denotes the short time window function with a sliding window variable τ and frequency component of signal f [13].

2.3.2 SPWVD

SPWVD is obtained by applying a smoothed window function to Wigner-Ville Distribution (WVD) [13]. The mathematical representation of WVD of a signal is defined as:

$$\boldsymbol{WVD(t,f) = \int_{-\infty}^{+\infty} R_x(t,\tau)\, e^{-j2\pi f\tau} d\tau} \quad (2)$$

Where $R_x(t,\tau)$ denotes the autocorrelation function. Even though WVD has high time and frequency resolution, the output is difficult to interpret due to cross-term interference caused by the interaction of two signal components. Smoothing windows are used to eliminate interference in WVD, which is referred to as SPWVD [13]. The mathematical representation of SPWVD is given as follows:

$$\boldsymbol{SPWVD(t,f) = \iint h(t-\tau) g(f-\delta) WVD(\tau,\delta) d\tau d\delta} \quad (3)$$

Where $g(t)$, and $h(t)$ represent the time and frequency-smoothing windows, respectively.

2.3.3 CWD

CWD [13] employs a kernel function (smooth window function) for Cohen class time-frequency distribution to eliminate the influence of cross-term interference. The kernel function used in CWD is in exponential form and is given as:

$$\boldsymbol{g(v,\tau) = e^{\frac{-v^2\tau^2}{\sigma}}, \sigma > 0} \quad (4)$$

The determining function $G(t,\tau)$ becomes:

$$\boldsymbol{G(t,\tau)} = \frac{\sqrt{\sigma/\pi}}{2\pi} e^{-\sigma t^2/4\tau^2} \tag{5}$$

Where σ is associated with the smoothing effect and regulates cross-term reduction and $(\boldsymbol{\tau - \nu})$ denotes the plane in ambiguity domain analysis [13].

2.3.4 Feature extraction

Four features, namely, mean (M), variance (Var), skewness (Sk), and kurtosis (Ku), are extracted from the TF spectrogram of individual methods. Table 1 shows the mathematical representations of each feature.

Table 1: *Statistical features.*

SI.NO	Feature	Expression
1	M [14]	$F_1 = \frac{1}{MN}\sum_M \sum_N P[n,k]$
2	Var [14]	$F_2 = \frac{1}{MN}\sum_M \sum_N (P[n,k] - F_1)^2$
3	Sk [14]	$F_3 = \frac{1}{(MN-1).s^3}\sum_M \sum_N (P[n,k] - F_1)^3$
4	Ku [14]	$F_4 = \frac{1}{(MN-1).s^4}\sum_M \sum_N (P[n,k] - F_1)^4$

Where, P[n, k] is the power spectrum of n^{th} time sample at the frequency bin k and $\boldsymbol{s}$ represents the time-frequency standard deviation

2.3.5 Classification

The statistical features extracted from each TF distribution method are fed to the four machine learning algorithms, namely Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) have been used for the classification. NB classifies data based on Bayes theory. It categorizes the data using the conditional independence probability approach. In LR, the predictions are in the form of probabilities. The probability of occurring of an event is obtained using a standard logistic function [4]. SVM uses a discriminating hyperplane to differentiate between two data classes. RF constructs several decision trees on the given data samples and predicts the class by voting each decision tree result [15].

Two classification evaluation metrics, namely F-measure (F-m) and area under the curve (AUC), have been used to assess each classifier performance. The proposed approach is tested for reliability using the K-fold cross-validation technique with K=10 [15].

3 Results and discussion

The representative phasic components obtained using the cvxEDA algorithm for happy and sad emotional states are shown in Fig. 2(a) and Fig. 2(e) correspondingly. A higher amplitude is observed in the phasic component of happy stimulus-response than sad stimulus-response, which may be attributed to increased sweat gland activity during happiness. However, these variations are subject-dependent.

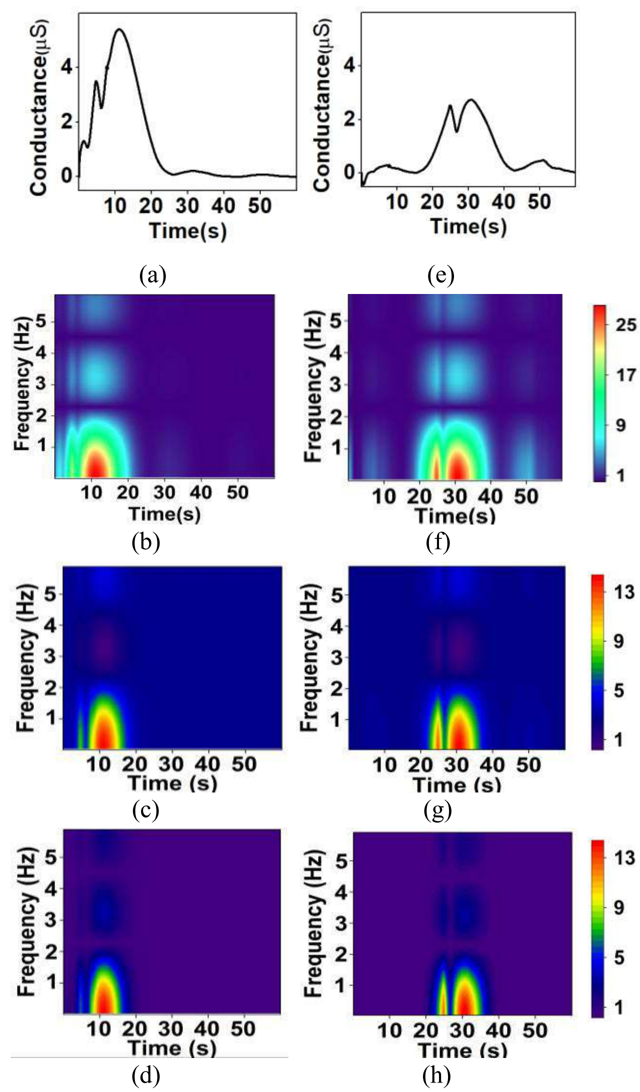

Figure 2: Representative phasic component of (a) happy and (e) sad emotional states and their corresponding TF distributions (b, f) STFT, (c, g) SPWVD, (d, h) CWD.

Furthermore, the TF distribution of the phasic component in happy and sad emotions using STFT, SPWVD, and CWD are shown in Figure 2(b, f), Figure 2(c, g), and Figure 2(d, h) correspondingly. Figure 2(b, c, d) shows the TF distributions corresponding to the phasic component in a happy emotional state. The frequency components in these spectrums are less compared with spectrums of sad emotional state (Figure 2 (f, g, h)). Further, the spectral components of STFT, SPWVD, and CWD-based TF distributions also show significant differences. The resolution of the STFT-based TF distribution is relatively poor compared to SPWVD and CWD, which is due to the fixed size of the window.

The features computed from each TF distribution are fed to four machine learning algorithms for classifying happy and sad emotional states. The performance metrics, namely F-m and AUC are evaluated from the classifiers for each TF distribution and are shown in Table 1. It is seen that the RF yields the highest F-m and AUC of 68.74% and 71.30%, respectively, for classifying happy and sad emotional states using SPWVD features. To the best knowledge of authors, the differentiation of happy and sad emotional states in EDA signals for the DEAP database is not explored. In one of the study, the dichotomous emotions are classified by computing Hjorth and higher order crossing features for the EDA signals and the approach yielded an average accuracy of 85.70% [4].

Table 2: *The classification performance [%] of statistical features obtained from various TFDs using different machine learning techniques.*

TFD	STFT		CWD		SPWVD	
Classifier	**F-m**	**AUC**	**F-m**	**AUC**	**F-m**	**AUC**
NB	56.00	49.80	46.13	45.10	46.42	48.50
LR	**56.30**	**55.50**	49.29	45.80	55.14	56.20
SVM	46.90	46.90	**53.73**	51.70	61.64	61.00
RF	46.84	41.70	51.17	**59.20**	**68.74**	**71.30**

4 Conclusion

This work introduces the TF techniques, including STFT, SPWVD, and CWD, and its statistical features for emotion analysis using EDA signals and comparing their classification performance using machine learning algorithms. The results indicate that all of the proposed TF methods are capable of representing non-stationary EDA signal fluctuations. The performance of various classifiers is evaluated from the features obtained from each TF distribution. In classifying happy and sad emotional states, the combination of features extracted from SPWVD and RF is most accurate.

Author Statement

Research funding: The author state no funding is involved. Conflict of interest: Authors state no conflict of interest.

References

[1] Hockenbury DH, Hockenbury SE. Disc psych. Macmillan. 2010.

[2] Veeranki YR, Kumar H, Ganapathy N, Natarajan B, Swaminathan R. A Systematic Review of Sensing and Differentiating Dichotomous Emotional States Using Audio-Visual Stimuli. *IEEE Access*, 9:124434-124451, 2021.

[3] Arias JA, Williams C, Raghvani R, Aghajani M, Baez S, Belzung C, Booij L, Busatto G, Chiarella J, Fu CH, Ibanez A. The neuroscience of sadness: A multidisciplinary synthesis and collaborative review. *Neurosci. and Biobeh. Rev.* 111:199-228, 2020

[4] Veeranki YR, Ganapathy N, Swaminathan R. Differentiation of dichotomous emotional states in electrodermal activity signals using higher-order crossing features and parametric classifiers. *Biomed. Sci. Instr*. 57(2):322-332, 2021.

[5] World Health Organization. Depression and other common mental disorders: global health estimates. World Health Organization. 2017.

[6] Posner J, Russell JA, Peterson BS. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Develop. and psychopath*. 17(3):715-34, 2005.

[7] Candra H, Yuwono M, Handojoseno A, Chai R, Su S, Nguyen HT. Recognizing emotions from EEG subbands using wavelet analysis. *In international conference of the IEEE engineering in medicine and biology society (EMBC)* pp. 6030-6033, 2015.

[8] Ganapathy N, Veeranki YR, Swaminathan R. Convolutional neural network based emotion classification using electrodermal activity signals and time-frequency features. *Exp. Sys. with Appl.*159:113571, 2020.

[9] Hu Y, Converse C, Lyons MC, Hsu WH. Neural control of sweat secretion: a review. *Brit. J. of Derm.*178(6):1246-56, 2018.

[10] Posada-Quintero HF, Chon KH. Innovations in electrodermal activity data collection and signal processing: A systematic review. *Sens.* 20(2):479, 2020.

[11] Koelstra S, Muhl C, Soleymani M, Lee JS, Yazdani A, Ebrahimi T, Pun T, Nijholt A, Patras I. DEAP: A database for emotion analysis using physiological signals. *IEEE trans. on aff. comp*. 3(1):18-31, 2011.

[12] Greco A, Valenza G, Lanata A, Scilingo EP, Citi L. cvxEDA: A convex optimization approach to electrodermal activity processing. IEEE Trans. on Biomed. Eng., 63(4):797-804, 2015.

[13] Subasi A. Practical guide for biomedical signals analysis using machine learning techniques: A MATLAB based approach. *Academic Press*. 2019.

[14] Sameer M, Gupta B. Detection of epileptical seizures based on alpha band statistical features. *Wireless Person. Commun.* 115(2):909-25, 2020.

[15] Veeranki YR, Ganapathy N, Swaminathan R. Non-Parametric Classifiers Based Emotion Classification Using Electrodermal Activity and Modified Hjorth Features. *Stud. in Health Techn. and Inform*. 281:163-7, 2021.