Assessment of Human Emotional States by Optimizing the Electrodermal Activity Signals with Two-dimensional Representations and Machine Learning

Thesis submitted in partial fulfilment

for the Award of

DOCTOR OF PHILOSOPHY

by

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SRIRAM KUMAR P

Abstract

Keywords: Emotion, Emotion recognition, Electrodermal activity, Decomposition, Segmentation, Windowing, Temporal features, Time-frequency representation, Time-encoded images, Machine learning

Emotions are fundamental aspects of human life that influence our thoughts, behaviors, and interactions with the world around us. Recognizing and understanding emotions is crucial in various aspects of life, including interpersonal relationships, mental health, and decision-making processes. Emotion detection holds significant importance in fields such as psychology, healthcare, and human-computer interaction. There are several ways to detect emotions, from traditional methods like facial expressions and vocal intonations to physiological signals such as Electrodermal Activity (EDA). It reflects changes in the skin's electrical conductance in response to emotional stimuli.

The EDA consists of several components, including tonic and phasic signals, which are influenced by the sympathetic nervous system activity associated with emotional states. For instance, variations in tonic signals may indicate overall arousal levels, while phasic signals represent rapid changes in arousal in response to specific stimuli. It is essential to understand the influence of EDA components, such as tonic and phasic signals for effective emotion detection. EDA signals are often complex and noisy, making it challenging to extract meaningful information. Segmenting the EDA signal into smaller, more manageable segments allows for targeted analysis of specific emotional responses. Hence, it is necessary to identify the significant segments of EDA signals to enhance emotion detec-

tion. Another important consideration is the windowing approach for EDA signals. Windowing involves dividing the continuous EDA signal into overlapping or non-overlapping windows for analysis. For instance, overlapping windows may capture temporal dynamics more effectively, while non-overlapping windows offer simpler processing but may miss transient emotional responses. The choice of windowing technique can significantly impact the effectiveness of emotion recognition algorithms. In this study, we attempted to identify the optimal component of the EDA signal and decomposition method, segment, and windowing approach using advanced signal processing methods and machine learning algorithms.

Initially, we obtained EDA signals from the publicly available Continuously Annotated Signals of Emotion (CASE) dataset for a 4-class categorical emotional classification. These signals underwent pre-processing, including applying a Butterworth low-pass filter with a 2 Hz cutoff frequency. We conducted three analyses to optimize EDA component and decomposition method, segment, and windowing approach as follows:

1) We employed convex optimization and Bayesian EDA decomposition methods to separate EDA signals into tonic and phasic components, then extracted ten temporal features from each component.

2) We considered the First-half, Second-half, and Whole phasic signals, generating spectrograms using the Short-Time Fourier Transform and Mel Frequency Cepstrum on considered signals. Features like Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) were extracted from these spectrograms.

3) We applied five and nine windows approaches with 50% overlapping on the Second half of the phasic signals. Then, each window of the time series signal was transformed into time-encoded images using the Gramian Angular Summation method, Gramian Angular Difference method, Markov Transition Field, and Recurrence Plot. From these images, we extracted features, including GLCM, GLRLM, fractal dimension texture analysis, Zernike's moments, Hu's moments, and first-order statistics.

Finally, we selected only the most significant features (p<0.05) of respective analyses obtained through the Kruskal-Wallis test. We applied these features independently to the three machine learning models, such as Support Vector Machine (SVM), Random Forest (RF), and XGBoost (XGB), to optimize the EDA components and decomposition method, segment and windowing approach.

Our findings revealed that phasic signals of EDA contributed well to emotion detection compared to the tonic component. The phasic signals decomposed by the cvxEDA decomposition method significantly impacted emotional state classification compared to the BayesianEDA method. We achieved an impressive accuracy of 86.87% with XGB, showcasing the method's efficacy in capturing relevant signals for emotion detection. Further, the Second half of the phasic signals contribute more information to emotion detection than the First half and Whole phasic signals. We achieved a remarkable classification accuracy of 97.08% with the SVM classifier. Finally, the nine windows of the Second half of phasic signals significantly improved emotion detection compared to the five-windows approach. We achieved a comparable accuracy of 88.24% using XGB. Our results underscore the importance of optimizing the EDA components, decomposition method, segments, and windowing approach to refine the emotion recognition systems and enhance classification performance.

The findings of this study offer substantial potential for a wide range of applications. These include healthcare monitoring systems, human-computer interaction interfaces, education and learning platforms, stress management and wellness mobile applications, virtual reality and augmented reality experiences, and the automotive and transportation industry. By integrating our advanced emotion recognition system, these applications can be significantly enhanced, leading to improved user experiences, greater well-being, and increased innovation across various industries.

Contents

List of Figures

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List of Abbreviations

2D: Two-dimensional

3D: Three-dimensional

ANS: Autonomic Nervous System

ASM: Angular Second Moment

AUC: Area Under the Curve

AV: Audio-visual

BVP: Blood Volume Pulse

CASE: Continuously Annotated Signals of Emotion

CDA: Continuous Decomposition Analysis

CNN: Convolutional Neural Networks

CNS: Central Nervous System

CWD: Choi–Williams Distribution

cvxEDA: Convex Optimization based on EDA

CWT: Continuous Wavelet Transform

DDA: Discrete Decomposition Analysis

DCM: Dynamic Causal Modeling

DR: Dynamic Range

ECG: Electrocardiogram

EDA: Electrodermal Activity

EEG: Electroencephalogram

EMG: Electromyogram

ER: Emotion Recognition

FDTA: Fractal Dimension Texture Analysis

FOS: First-Order Statistics

GADF: Gramian Angular Difference Field

GAF: Gramian Angular Field

GASF: Gramian Angular Summation Field

GLCM: Gray Level Co-occurrence Matrix

GLRLM: Gray Level Run-Length Matrix

GLU: Gray-Level Uniformity

HM: Hu's Moments

HR: Heart Rate

HRV: Heart Rate Variability

HVHA: High Valence/High Arousal

HVLA: High Valence/Low Arousal

KNN: K-Nearest Neighbors

KW: Kruskal-Wallis

LR: Logistic Regression

LRE: Long Run Emphasis

LTI: Linear Time-Invariant

LVHA: Low Valence/High Arousal

LVLA: Low Valence/Low Arousal

MAP: Maximum Peak

MASM: Mean of Angular Second Moment

MCN: Mean of Contrast

MCR: Mean of Correlation

MDE: Mean of Difference Entropy

MDN: Median

MDV: Mean of Difference Variance

ME: Mean of Entropy

MFD: Mean of First Derivative

MFCC: Mel-Frequency Cepstral Coefficients

MFC: Mel-Frequency Cepstrum

MIDM: Mean of Inverse Difference Moment

MIMC1: Mean of Information Measures of Correlation-1

MIMC2: Mean of Information Measures of Correlation-2

MIP: Minimum Peak

ML: Machine Learning

MN: Mean

MMCC: Mean of Maximal Correlation Coefficient

MSA: Mean of Sum Average

MSD: Mean of Second Derivative

MSE: Mean of Sum Entropy

MSV: Mean of Sum Variance

MSSV: Mean of Sum of Squares Variance

MTF: Markov Transition Field

PNS: Peripheral Nervous System

RASM: Range of Angular Second Moment

RCN: Range of Contrast

RCR: Range of Correlation

RDE: Range of Difference Entropy

RDV: Range of Difference Variance

RE: Range of Entropy

RIDM: Range of Inverse Difference Moment

RIMC1: Range of Information Measures of Correlation-1

RIMC2: Range of Information Measures of Correlation-2

RLU: Run Length Uniformity

RMCC: Range of Maximal Correlation Coefficient

RPC: Run Percentage

RP: Recurrence Plot

RSA: Range of Sum Average

RSE: Range of Sum Entropy

RSP: Respiration

RSV: Range of Sum Variance

RSSV: Range of Sum of Squares Variance

SAM: Self-Assessment Manikin

SFD: Standard Deviation of First Derivative

SKT: Skin Temperature

SparsEDA: Nonnegative Sparse Deconvolution

SRE: Short Run Emphasis

SSD: Standard Deviation of Second Derivative

SS: Sum of Squares

STD: Standard Deviation

STFT: Short Time Fourier Transform

SVM: Support Vector Machine

TFR: Time-Frequency Representation

VA: Valence-Arousal

WVD: Wigner–Ville Distribution

XGB: XGBoost

ZM: Zernike's Moments

List of Symbols

A : State transition matrix

B : Tall matrix containing cubic B-spline basis functions as columns

C : Observation matrix

C_P : Coefficient matrix for the phasic component

C_T : Coefficient matrix for the tonic component

$T(t)$: Diffusion/reabsorption

D_{ij} : Euclidean distance between any two points in the phase space

f : Frequency

f : Linear frequency

f_m : Mel-frequency

H : Matrix representation in the Laplace transform of $h(t)$

$H_m(f_k)$: Value of the m-th triangular filter at frequency f_k

$h(t)$: Impulse response shaped as a bi-exponential Bateman function

I : Current

j : Imaginary unit

l : Vector of spline coefficients

M : Tridiagonal matrix with moving average coefficients

M_{ij} : Element of the MTF matrix representing the transition probability based on the time order of the original time series

$P(t)$: Phasic component

p : Sudo Motor Nerve Activity (SMNA)

q : Auxiliary variable

q : Vector in optimization problems

$q(x_i)$: Bin to which the value x_i belongs

R : Recurrence matrix

R : Skin resistance

r : Phasic activity

ri : Radius in polar coordinates

$S(t)$: Sweat secretion via pore opening

$S(f_k, t)$: Spectrogram magnitude at frequency f_k and time t

$SC(t)$: Skin conductance at time t

$SC_P(t)$: Phasic component of skin conductance at time t

$SC_T(t)$: Tonic component of skin conductance at time t

t : Tonic component

τ : Delay coefficient in phase space reconstruction

τ : Variable representing time in STFT

τ_1 : Slow time constant of the phasic curve shape

τ_2 : Fast time constant of the phasic curve shape

$u(t)$: Unitary step function

u_k : Input at discrete time step k

U : Heaviside step function

V : Voltage

W : Markov transition matrix

$w(t-\tau)$: Window function in STFT

w_{ij} : Probability of transitioning from bin i to bin j

X : Original time series data

X : Time series data

$X(t)$: Time series data

$\hat{X}$: Normalized time series

$x(t)$: Time-domain signal

x_k : State variable at discrete time step k

ϵ : Additive independent and identically distributed zero-average Gaussian noise term

ϵ : Threshold distance in phase space reconstruction

μS : MicroSiemens

ϕ : Angle

ϕ_i : Polar angle corresponding to the i-th element of the time series

$\nu(t)$: Observation noise at time t

ν_k : Observation noise at discrete time step k