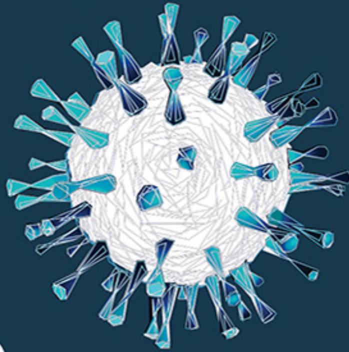

Digital Technology in PUBLIC HEALTH AND REHABILITATION CARE

COVID Era

Edited by
Raymond K.Y. Tong
Balasankar Ganesan

Digital Technology in Public Health and Rehabilitation Care

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COVID Era

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Preface

Digital technology has permeated nearly every aspect of modern life and nowhere has its impact been more profound than in the realms of public health and rehabilitation care, especially in the wake of the COVID-19 pandemic. The rapid spread of the virus and the subsequent need for remote healthcare solutions have accelerated the adoption of digital technologies across the healthcare spectrum. In this book, *Digital Technology in Public Health and Rehabilitation Care: COVID Era*, we delve into the intricate ways in which digital innovations have transformed healthcare delivery during these unprecedented times.

From mobile phones to artificial intelligence, from wearable sensors to virtual reality, a myriad of digital tools has been harnessed to address the challenges posed by the pandemic. Through a comprehensive examination of case studies and insights, this book offers a panoramic view of the diverse applications of digital technology in public health and rehabilitation services.

The COVID-19 crisis has underscored the critical importance of access to quality healthcare for all, particularly for vulnerable populations such as older adults, individuals with disabilities, and those with underlying health conditions. As traditional modes of rehabilitation services faced disruptions, digital solutions emerged as a beacon of hope, offering novel ways to deliver care remotely.

In this book, we explore how digital technologies have facilitated remote monitoring, telehealth consultations, virtual therapy sessions, and personalized interventions, bridging the gap between patients and healthcare providers. Furthermore, we examine the potential of emerging technologies such as robotics, 3D printing, thermal imaging, virtual and augmented reality, and other computer games to revolutionize rehabilitation practices, enabling tailored interventions that cater to individual needs.

However, while digital technology offers immense promise, its widespread adoption comes with its own set of challenges and considerations. Issues such as digital literacy, data privacy, and equitable access to technology must be addressed to ensure that no one is left behind in the digital transformation of healthcare.

As we navigate through this era of uncertainty and change, it is imperative for researchers, healthcare professionals, and policymakers to collaborate in harnessing the full potential of digital innovations for public health and rehabilitation care. By leveraging the power of technology, we can not only mitigate the impact of the current crisis but also lay the groundwork for a more resilient and inclusive healthcare system for the future.

We hope that this book serves as a valuable resource for anyone interested in understanding the intersection of digital technology and healthcare, offering insights and inspiration for building a healthier and more connected world.

Raymond K.Y. Tong
Balasankar Ganesan

CHAPTER 17

Optimizing electroencephalography-emotion classification through strategic window selection methodology

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Learning outcomes

Using the window selection methodology in EEG-emotion recognition will gain knowledge and understanding of the following:

- Temporal analysis: Researchers can perform temporal analysis to capture changes in brain activity over time by segmenting Electroencephalography (EEG) data into smaller windows. The segmentation allows for identifying patterns and fluctuations in EEG signals associated with different emotional states.
- Feature extraction: Window segmentation enables extracting relevant features from EEG signals within each window. This act is similar to zoom-in or zoom-out into the elements. These features may include spectral, time domain, or spatial features that can be input for machine learning algorithms. Extracting features from segmented windows helps in capturing the dynamic nature of emotions.
- Improved classification: Machine learning algorithms, such as support vector machines or deep neural networks, are frequently used for EEG-emotion recognition. Window segmentation contributes to a structured way to train and test the algorithms to enhance the performance of emotion classification models. By analyzing individual windows, classifiers can better capture the nuances of emotional transitions.
- Noise reduction: EEG signals are susceptible to noise and artefacts caused by various origins, for example, muscle movements or electrical interference. Window segmentation allows researchers to insulate and analyze EEG data segments more clearly by reducing noise's impact on emotion recognition accuracy.

17.1 Introduction

The coronavirus pandemic altogether affects the psychological wellness and close-to-home prosperity of individuals all over the planet. Social isolation, uncertainty, anxiety, and stress brought on by significant lifestyle shifts are some of the contributing factors to this issue. A study by Huang and his colleagues found that the COVID-19 pandemic has made mental

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health issues and emotional disorders like posttraumatic stress disorder, anxiety, and depression more common (Huang & Zhao, 2020). The COVID-19 pandemic's mental and emotional disturbances can be overcome by recognizing and comprehending one's emotions. During the COVID-19 pandemic, emotion detection technologies like sentiment analysis and machine learning can be utilized to identify and track emotional shifts. Emotion detection technology can help improve mental health services and monitor individual mental health during the COVID-19 pandemic, according to a study by Wang et al. (2020).

Attempts to recognize human emotions have been made in numerous ways utilizing diverse physiological signals (Katsis, Katertsidis, & Fotiadis, 2011; Yang & Lugger, 2010; Valenza, Lanata, & Scilingo, 2012; Singh, Conjeti, & Banerjee, 2013; Wen et al., 2014). Among them, the most widely studied is the brain waves or EEG (Yuvaraj et al., 2014; Iacoviello, Petracca, Spezialetti, & Placidi, 2015; Soleymani, Asghari-Esfeden, Fu, & Pantic, 2016; Xing et al., 2019; Qing, Qiao, Xu, & Cheng, 2019) as experts already know that the brain is the primary source of emotion (Panksepp, 2010). One major challenge with EEG is its time-varying and nonstationary characteristics.

One possible way to manage this trouble is to divide these signals into more modest window outlines so that design reiterations can be separated all the more effectively (Picard, Vyzas, & Healey, 2001). Having a constant mean and variance in a short time window is a desirable statistical property of a pseudostationary signal. Pseudostationary signal predictions will likely have a higher predictive power (Kaplan, Fingelkurts, Fingelkurts, Borisov, & Darkhovsky, 2005). By "zooming in" on the recurring pattern of emotion elicitation, we aim to maximize the information gained with our proposed window size optimization technique. The window size should be perfect: A window that is too short will result in incompleteness, whereas a window that is too long will result in an excessive inclusion of nonstationary parts.

One method for demonstrating emotions—for example, that depicted by Russel—is through layered planes. A well-known model of emotion, Russell's circumplex model of affect (Russell, 1980), divides an emotion into arousal (activate-deactivate) and valence (pleasant-unpleasant) two-dimensional planes (Barrett & Bliss-Moreau, 2009). A model use of this model is framed by Nardelli et al., who exhibit changes in heart rate variability that are statistically significant between emotion representations in the arousal-valence plane (Nardelli, Valenza, Greco, Lanata, & Scilingo, 2015).

EEG-based emotions classifiers can be fabricated utilizing calculations, for example, straight discriminant investigation using Linear Discriminant Analysis (LDA), head part examination using Principal Component Analysis (PCA), fake brain organizations using Artificial Neural Network (ANN), backing vector machines using Support Vector Machineeog (SVM), or a mix of the strategies (Bhardwaj, Gupta, Jain, Rani, & Yadav, 2015; Thejaswini, Ravi Kumar, Rupali, & Abijith, 2018; Guo et al., 2019; Ullah et al., 2019). Due to its ability to work with nonlinear and high-dimensional feature spaces, SVM is an effective classifier for the task (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007). This manuscript used the Russel model and SVM classifier to classify EEG emotion.

Fast Fourier transform (FFT) and wavelet transform (WT) are standard features used in EEG signal analysis (Akin, 2002; Candra, Setyaningsih, Pragantha, & Smieee, 2019). The numerous advantages of the WT when compared to FFT are as follows (Rosso et al., 2001):

- Wavelet entropy is fit to distinguish the frequency of an example by assessing fragment consistency.
- The estimated wavelet coefficient can be utilized to decide the construction of an example.
- The bandpass filter and noise removal are combined in the WT. With WT, an EEG sign can be effectively decayed and secluded to incorporate just the data from the ideal subband. This property is significant for recognizing emotions because beta and gamma frequencies correlate more strongly with emotion than other subbands (Zheng & Lu, 2015; Candra, Yuwono, Handojoseno, et al., 2015).

WT has been exhibited to be an integral asset for time-basic EEG highlight extraction during freezing of stride episodes (Ardi Handojoseno et al., 2015) as well as epileptic seizures.

An approach to streamlining an EEG emotions order framework's consistent quality is presented in this paper. Using a straightforward feature-agnostic time window optimization strategy, we will demonstrate that an increase in accuracy that is consistent and ranges from 3% to 15% can be achieved. Six different features are extracted from the subjects, and each technique is explained, compared, and analyzed. In order to meet our goal of selecting the best feature and window size, we use SVM as the classifier of a decision in the experiment. In order to find the shorter processing time, an analysis of the training and testing processing times is also discussed. The findings point to a window size most effective for EEG-emotion classification and its correlated time processing.

This paper's novel contributions include the following:

- To start with, we exhibit that using our proposed highlight rationalist prehandling technique: an EEG classification system's accuracy can be further enhanced with optimal window selection (OWS).
- In the second part of the paper, we use emotion recognition as an example application to show how our method may be able to address the nonstationary behavior of EEG signals.
- Thirdly, we propose a novel wavelet feature that combines segment average wavelet approximation coefficients and wavelet entropy.

According to our experiments, SVM classifiers trained with these novel features consistently produce significantly higher results than those trained with features like simple average, FFT, and wavelet energy.

The remaining parts of the paper are laid out as follows: The dataset and its preparation for the experiment are discussed in detail in Section 17.2. Section 17.3 depicts the top to bottom of the strategy, including subject determination calculation, signal division process, insights concerning the element extraction calculations, and the preparation and testing conventions. Section 17.4 gives the investigation and conversation of the exploratory outcomes. The conclusion and future directions are covered in Section 17.5.

17.2 Dataset

17.2.1 Data source

The Dataset for Emotion Analysis Using Electroencephalogram, Physiological, and Video Signals (DEAP) from Koelstra et al. is utilized in this study (Koelstra et al., 2012), which was made available with the authors' permission. The dataset gives multimodal information on human emotional states investigation from 32 participants. The volunteers were asked to watch 41-min sections of music videos while their signals were recorded. Electrooculography (EOG), Electromyography (EMG: zygomaticus major and trapezius muscles), Galvanic Skin Response (GSR: left middle and ring fingers), respiration belt, plethysmograph (left thumb), and temperature are the signal sources. During the experiment, 22 out of 32 participants had their frontal faces recorded. To depict their sentiments regarding valence, arousal, dominance, liking, and familiarity, the participants gave every music video a persistent value somewhere between 1 and 9. Standardized Self-Assessment Manikins (SAM) was used for the evaluation (Bradley & Lang, 1994).

Koelstra finished EEG preprocessing (Koelstra et al., 2012) such as:

Resampling to 128 Hz,

Expulsion of EOG antiquities utilizing blind source detachment,

Filtering using 4.0−45.0 Hz bandpass filter, and

Using a standard reference as an average for the data.

17.2.2 Subject grouping

Although self-reports of emotions utilizing SAM are probably going to be legitimate for currently experienced emotions, the clients might find it trying to decipher and relate the pictures utilized in SAM to their emotions, so a reasonably comparative EEG example might be converted into very going against emotions which lead to the debasement of the unwavering order quality (Isomursu, Tähti, Väinämö, & Kuutti, 2007). As a result, as described in the method section, we conducted subject grouping to appropriately select a group of participants for the experiment to reduce the effect of mistranslation.

Online ratings, a video list, and participant questionnaires are also essential components of the dataset that can be used to comprehend it. The EEG data preprocessed using Koelstra's preprocessing method (Koelstra et al., 2012) were also available in MATLAB® and Python formats. The experiment made use of this preprocessed data.

17.3 Methods

This section will provide a more in-depth explanation of how the experiment was carried out. We began by performing subject gathering and EEG signal division. We went on with highlight extraction utilizing different strategies, including statistical features, the FFT, and the discrete wavelet transform (DWT) SVM classification which was the experiment's final step. To all the more likely comprehend how the trial was directed, we have isolated this segment into the accompanying six subsections:

Grouping by subject

Emotional EEG signals are divided into 12 windows of size

Feature extraction using the DWT

Statistical characteristics: naive mean of the time domain signal (MTD) and mean wavelet approximation coefficients with wavelet entropy (MAE)

FFT power spectral density (PSD)

Training and testing with SVM classifier

The experiment aimed to determine the feature extractor and window size with the highest accuracy for an SVM emotion classifier. As shown in Fig. 17.1, grid search was used to optimize these two parameters. The strategy was as per the following:

Subject grouping: Applying are bunched given how firmly related every individual is to one more and placed in bunches with dendrogram the radial basis function (RBF) piece capability (Schölkopf, Tsuda, & Vert, 2004) to determine the transformation matrix of each individual's EEG features concerning their emotion rating. The outcome is fitted as calculated relapse. The matrices for clustering are created by

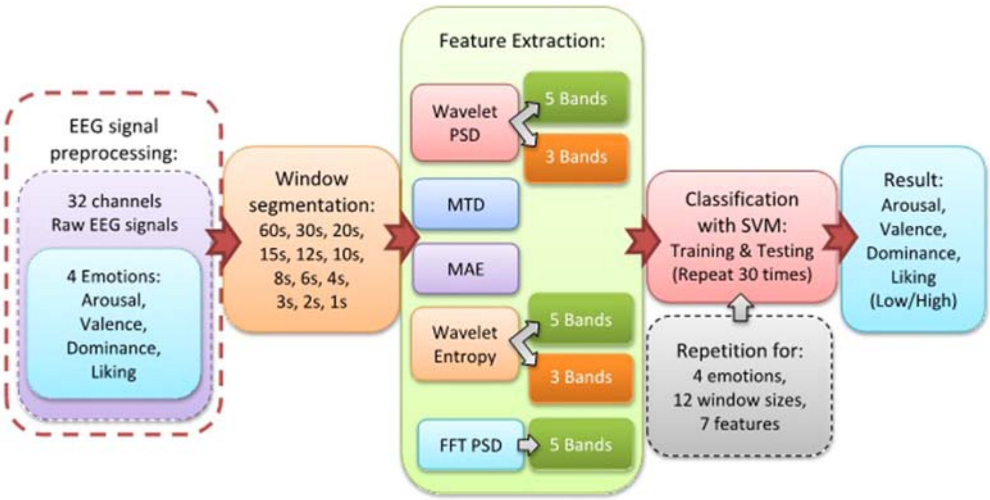

Figure 17.1 Flow diagram of optimal window selection process. The step by step process to obtain the optimal window.

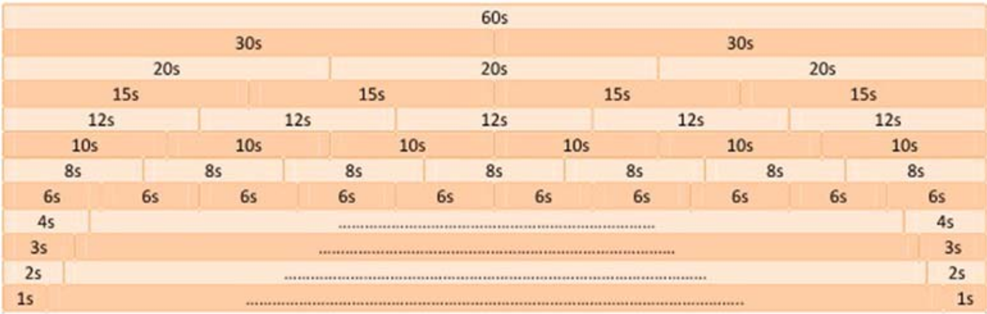

Figure 17.2 Segmentation with 12 window sizes. The sizes of the windows used in the experiment.

concatenating all participant results. These matrices are used for mapping the relation between each person to another and put in groups with dendrogram.

Segmenting the signal: First, the preprocessed EEG signal was segmented into 12 window sizes: $t \in \mathbb{T}:\mathbb{T} = 1, 2, 3, 4, 6, 8, 10, 12, 15, 20, 30, 60$ (in seconds). The video length, or 60 s, was the upper limit for this parameter. The rule $N = 60/t$ is observed in the number of segments produced (see Fig. 17.2).

Feature extraction: Consider the following mapping of a preprocessed EEG signal segment $\mathbf{s}_n$ to its feature vector representation $\mathbf{x}_n$ as a function of a feature extractor:

$$f(\mathbf{s}_n) \mapsto \mathbf{x}_n. \tag{17.1}$$

The *feature extractor* considered in this paper includes the following:

1. and three bands[1] wavelet PSD,
2. Five and three bands[1] wavelet entropy (Candra, Yuwono, Chai, et al., 2015),
3. naive **M**ean of the **T**ime **D**omain signal (MTD), and
4. **M**ean wavelet **A**pproximation coefficients with wavelet **E**ntropy (MAE),
5. Additional FFT PSD (five bands) features was accommodated to compare with other feature.

Classification of emotion and evaluation

1. Labeled set construction

   For a given emotion[2] $z \in \mathbb{A}:\mathbb{A} = vl, ar, do, lk$, the ratings given to a video v were mapped to a category label $c_{z,v}$ using the following rule:

$$c_{z,v} = \begin{cases} \mathit{Lo}\text{if} & 1 \le v \le 4.5, \\ \mathit{Hi}\text{if} & 4.5 < v \le 9. \end{cases} \tag{17.2}$$

[1] 5 EEG bands: delta, theta, alpha, beta, and gamma. 3 EEG bands: alpha, beta, and gamma.
[2] Valence. arousal. dominance, liking.

The associated feature vectors for this category were then mapped, producing a set of labeled points,[3] $\mathbb{X}_z : z \in \mathbb{A}$:

$$\mathbb{X}_z(v) = (c_{z,v}, \mathbf{x}_1), (c_{z,v}, \mathbf{x}_2), (c_{z,v}, \mathbf{x}_N), \tag{17.3}$$

where N denotes the number of segments. The overall dataset $\mathbb{X}$ is the union of labeled points for each video:

$$\mathbb{X}_z = \bigcup_1^V \mathbb{X}_z(v) \tag{17.4}$$

2. Training and testing

The datasets were haphazardly parted into a training set (30%) and a test set (70%). SVM was prepared to utilize the training set. The test set evaluated the classification's sensitivity, specificity, and accuracy. Thirty times were spent on random sampling and retraining.

A total of 4 planes of emotion, 12 window sizes, 7 features, and 30 retraining resulted in the creation and dispatch of 10,080 parallel computation jobs.

A more detailed process on each step will be discussed in the following subsections.

17.3.1 Subject grouping

Let $\mathbb{X}_z(s) = (c_{z,1}, \mathbf{x}_1), (c_{z,2}, \mathbf{x}_2), (c_{z,N}, \mathbf{x}_N)$ be defined as a set of labeled points $\mathbb{X}_z$ produced by a specific subject s.

For any $\mathbf{x}$, let $\phi(\mathbf{x}, \mathbf{x}')$ be defined as an RBF kernel function (Schölkopf et al. 2004),

$$\phi(\mathbf{x}, \mathbf{x}'_m) = \exp\left(-\frac{||\mathbf{x} - \mathbf{x}'_m||^2}{2\sigma^2}\right) \tag{17.5}$$

where $\mathbf{x}'_m$ and σ denote the center and radius of the mth kernel, both assumed to be reasonably optimized.

Let $\mathbf{\Phi}(\mathbf{x})$ be a vector containing the evaluated results of the kernel function for each $\mathbf{x}'_m$, $m \in 1, M$,

$$\mathbf{\Phi}(\mathbf{x}) = \bigcup_m \phi(\mathbf{x}, \mathbf{x}'_m). \tag{17.6}$$

For any c_z, let $logit(c_z)$ be defined as follows:

$$logit(c_z) = \log\left(\frac{c_z}{1 - c_z}\right). \tag{17.7}$$

[3] A labeled point is a category-label—feature vector tuple: (c_v^z,x_n^z).

Let $\mathbf{c}$ be defined as a vector containing the four emotions' labels,

$$\mathbf{c} = \bigcup\nolimits_{z \in \mathbb{A}} c_z, \mathbb{A} \in vl, ar, do, lk. \tag{17.8}$$

The relation between $(\mathbf{c}_n, \mathbf{x}_n)$ can then be simplified as the following linear equation:

$$\mathbf{\Phi}(\mathbf{x}_n)\mathbf{P} = logit(\mathbf{c}_n) \tag{17.9}$$

where $\mathbf{P}$ is a $M \times 4$ matrix explaining the linear relationship between $\mathbf{\Phi}(\mathbf{x}_n)$ and $\mathbf{c}_n$. Assuming $\mathbf{C} = \mathbf{c}_1, \mathbf{c}_N$, $\mathbf{\Phi}(\mathbf{X}) = \mathbf{\Phi}(\mathbf{x}_1), \mathbf{\Phi}(\mathbf{x}_N)$, and since $\mathbf{\Phi}(\mathbf{X})$ is a rank matrix with all columns, we can then linearly solve $\mathbf{P}$ as follows:

$$\mathbf{P} = \left(\mathbf{\Phi}^T(\mathbf{X})\mathbf{\Phi}(\mathbf{X})\right)^{-1}\mathbf{\Phi}^T(\mathbf{X})logit(\mathbf{C}). \tag{17.10}$$

To look at the planning networks of every individual subject, we then, at that point, address $\mathbf{P}$ for each $\mathbb{X}_z(s)$. This cycle yields $\mathbb{P} = \mathbf{P}_1, \mathbf{P}_S$, where S is the number of subjects. The pairwise Euclidean distance between the $\mathbf{P}$ matrices is then calculated. The distance between subjects with similar response patterns will then be relatively close. We then, at that point, develop a dendrogram utilizing Ward's technique and separate the subjects into a few subgroups as indicated by the closeness of their frameworks. This paper's subject matter was then selected randomly from one of the subgroups.

17.3.2 The 12 window sizes for electroencephalography-emotion signals

In order to get ready for feature extraction, the preprocessed EEG signals were segmented. At the 60-s video clip length, the largest possible window size was upper bounded. This window was then cut in half, and it was cut in half every time from the previous window size until the smallest window was 1 s, which was limited by the sampling rate of 128 samples per second. In order to soften the investigation's conclusion, additional window sizes were added in between the sizes that had been previously chosen. Twelve sizes of windows can be accommodated: 60; 30; 20; 15; 12; 10; 8; 6; 4; 3; 2; and 1 s. Fig. 17.2 shows the window division process from biggest to smallest with 12 window sizes. The feature extraction procedure stores the segmentation results in a different dataset. Each segment was combined and used for feature extraction for each segmentation result, which multiplies the size of the data by the number of segments gathered.

17.3.3 Discrete wavelet transform feature extraction

The DWT is profitable; it might be said that it gives time-recurrence limitation, multi-scale zooming, and multirate separating for distinguishing and describing homeless people. Because of these advantages, DWT may be able to extract the relevant data from nonstationary signals like EEG signals (Candra, Yuwono, Chai, et al., 2015; Ardi Handojoseno et al., 2015).

The DWT uses the following dyadic scales and positions to decompose any one-dimensional time signal $x(t)$:

$$DW(x(t)a, n) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{2^a}} \psi\left(\frac{t - 2^a n}{2^a}\right) dt \tag{17.11}$$

where $2^a n$ and 2^a are the time localization and scale, respectively, while $\psi(t)$ denotes the mother wavelet function.

The DWT can be interpreted as a filtering process using a *dyadically* shifted and scaled mother wavelet.

17.3.3.1 Wavelet power spectral density

The energy of the wavelet coefficient located at the ath level of decomposition is measured by the wavelet PSD $E(a)$, which can be calculated as follows:

$$E(a) = \| C_a \|^2 = \sum\nolimits_n C_a^2[n] \tag{17.12}$$

where C_a denotes the wavelet coefficients at the ath decomposition level. C_a can be either x_{A_a} or x_{D_a}.

Normalizing the wavelet energy against the complete wavelet energy, a likelihood mass capability is gotten as follows:

$$\rho(a) = \frac{E(a)}{\sum_{K=1}^{K} E(K)}, \tag{17.13}$$

where K denotes the number of discrete wavelet decompositions, $\rho(a)\varepsilon\{0, 1\}$ and $\sum_a \rho(a) = 1$. This normalized measure is also known as the *relative wavelet energy/wavelet PSD* (Rosso et al., 2001).

17.3.3.2 Wavelet entropy

The degree of unpredictability in the energy distribution is measured by the wavelet entropy $H(a)$. Refer to Eq. (17.13) for the probability mass function $p(a)$ which is calculated as follows (Rosso et al., 2001):

$$H(a) = -p(a)\log p(a), \tag{17.14}$$

where K means the quantity of DWT decompositions.

17.3.3.3 Creating array formation of 32 channels five and three bands wavelet energy and entropy

Wavelet PSD and entropy's five and three bands are arranged in an array that combines all 32 channels and is related to a single EEG-emotion signal segment. Fig. 17.3 demonstrates this procedure.

17.3.4 Statistical features: MTD and MAE

The statistical features are represented in two variations:

17.3.4.1 Mean of the time domain signal

The statistical characteristics of MTD can be calculated by Picard et al. (2001b) using X_k to represent the amplitude from the kth sample in one channel preprocessed EEG-emotion signal.

$$\mu_x = \frac{1}{K}\sum\nolimits_{K=1}^{K} X_k \tag{17.15}$$

where $K = n(X)$ denotes the cardinality of X.

17.3.4.2 Mean wavelet approximation coefficients with wavelet entropy

The following formula can be used to calculate the mean of the wavelet approximation coefficient μ_A: Given a decomposition of the wavelet approximation coefficient at the ath level, $A_k = \text{approx}(DWT(x(t); a, k))$,

$$\mu_A = \frac{1}{K}\sum\nolimits_{K=1}^{K} A_k \tag{17.16}$$

where the cardinality of A is $K = n(A)$. For the MAE features, the EEG channel orders both μ_A and $H(a)$ concatenated into an array.

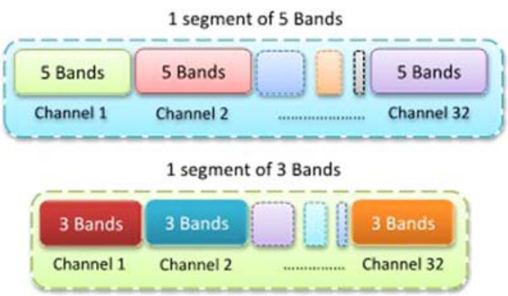

Figure 17.3 Array of 32 channels five and three bands wavelet PSD/entropy. The development of the features used for the experiment. *PSD*, Power spectral density.

17.3.5 Fast Fourier transform power spectral density

The Fourier transform of EEG signal *x(n)* can be extracted with

$$X(k) = \sum_{n=0}^{N-1} x(n) W_N^{kn} \tag{17.17}$$

where $W_N = e^{-j(2\pi/N)}$ and $N =$ length of the EEG signal, which varies based on the window size. Using these Fourier coefficients, the relative FFT PSD can then be obtained.

17.3.6 Training and testing with support vector machines classifier

The classification process with SVM classifier uses *RBF* kernel. Utilizing ensemble rapid centroid estimation (*ERCE*) (Yuwono, Su, Moulton, & Nguyen, 2014; Yuwono, Su, Moulton, Guo, & Nguyen, 2014), the kernel radius RSVM is inferred from the training data with the SVM radius estimation step as follows:

Let $\mathbf{p}_j{:}p \in \{0, 1\}$ be a probability vector that describes the wavelet entropy characteristics of the training set.

Put ERCE into action (Yuwono et al., 2014; 2014) to cluster $\mathbb{P} = \{\mathbf{p}_1, \mathbf{p}_2,\}$ corresponds to any number of clusters determined by the Jensen-Shannon distance.

Using an average linkage, combine the ensemble clustering results to produce the final clustered sets $\{\mathbb{C}_1 \cup \ \cup \mathbb{C}_K\}$, where K is determined automatically by ERCE during ensemble aggregation. The following is how the corresponding centroid vectors $\{\boldsymbol{\mu}_1, \boldsymbol{\mu}_K\}$ are computed,

$$\boldsymbol{\mu}_k = \frac{1}{|\mathbb{C}_k|} \sum\nolimits_{\mathbf{p} \in \mathbb{C}_k} \mathbf{p} \tag{17.18}$$

The *SVM* radius R_{SVM} is taken as the average cluster radius in terms of Euclidean distance as follows:

$$R_{\text{SVM}} = \frac{1}{K} \sum\nolimits_{k=1}^{K} \sum_{\mathbf{p} \in \mathbb{C}_k} \frac{||\mathbf{p} - \boldsymbol{\mu}_k||}{|\mathbb{C}_k|}. \tag{17.19}$$

The sequential minimal optimization (SMO) algorithm trains the SVM (Chang & Lin, 2011).

17.4 Result and discussion

Before discussing the experiment's results, it is necessary first to examine the steps involved to comprehend them. This part will initially show the fragmented EEG signal investigation utilizing a wavelet PSD spectrum. The next step is to compare MAE to other features and conduct a deeper analysis of the wavelet features. The discussion of the training and testing time with seven features and the method for selecting the best window continues here. The following are the six subsections that make up this section:

1. Representation of the segmented EEG-emotion signals in wavelet PSD spectrum
2. Classification with seven features
3. Analysis of wavelet features
4. Analysis of MAE compared to other features
5. Analysis of training and testing time for seven features
6. Suggested OWS in EEG-emotion classification with seven features for four emotions planes (arousal, valence, dominance, liking)

17.4.1 Representation of the segmented electroencephalography-emotion signals in wavelet power spectral density spectrum

One participant was chosen randomly to receive a single preprocessed EEG signal sample from a channel selected at random. The signs are pictured in their connected five stacked groups wavelet PSD range as displayed in Fig. 17.4, showing the correlation between the 60-s window and 15 successive 4-s windows. The combination of 15 4-s segments that come in succession makes up the 60-s segment. The 4-s segment, on the other hand, has 15 stacked wavelet PSD spectrums, while the 60-s segment only has one. The repetitional pattern in the 3rd, 7th, 10th, 14th, and 15th spectrums of the 4-s segment is comparable to that of the 60-s segment. This reiteration uncovers that portioned EEG signals with exact window size have a fixed example which is rehashed in the fragments with a more modest window size. However, the additional segments will also display an irregular pattern.

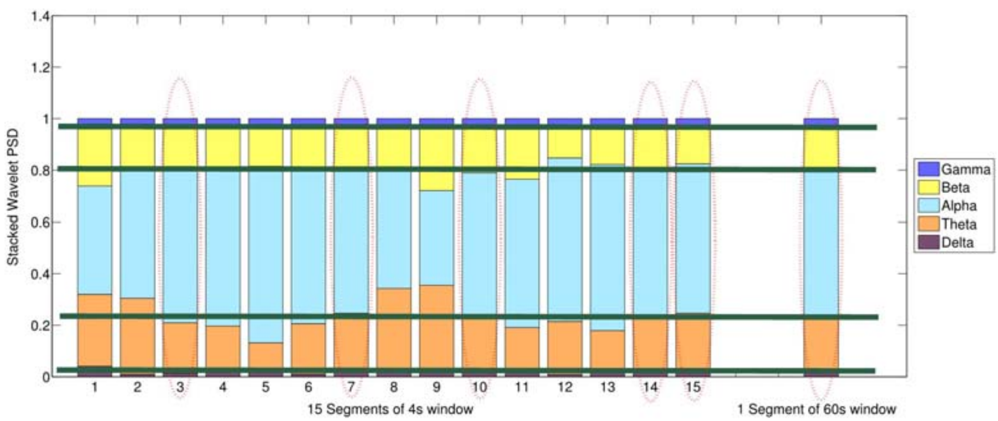

Figure 17.4 Perception of 1 divert EEG signals in their connected five stacked groups wavelet PSD range of 60-s window contrasted with 15 sequential 4-s window showing the repetitional design between the two windows. Comparison of 60-s wavelet PSD and 15 successive 4-s wavelet PSD. *EEG*, Electroencephalography; *PSD*, power spectral density.

17.4.2 Classification with seven features

Fig. 17.5 shows the classification results of four emotion planes using the six investigated features and the comparative FFT PSD features. The charts show that MAE highlight beats toward any remaining elements, including the similar FFT PSD highlight. Although the precision of every inclination has a different reach, in any case, they show a comparative pattern. The correctness starts with poor outcomes at the most significant 60-s window, after that increment somewhat between the 30- and 20-s window. The exactness arrives at the top between the 12- and 4-s window and diminishes again between the 3- and 1-s window.

Taking into account the comparative pattern of the four emotions planes displayed in Fig. 17.5, we worked on the charts of the four emotions planes for an additional examination of the window determination technique by taking the weighted normal of the four emotions planes for every one of the seven highlights and shows the outcomes in Fig. 17.6.

17.4.3 Analysis of wavelet features

We further investigate the connection between wavelet PSD and entropy in Fig. 17.6. The charts show that the five groups' wavelet entropy is more exact than the five groups' wavelet PSD. The gathering results show an augmentation with a more

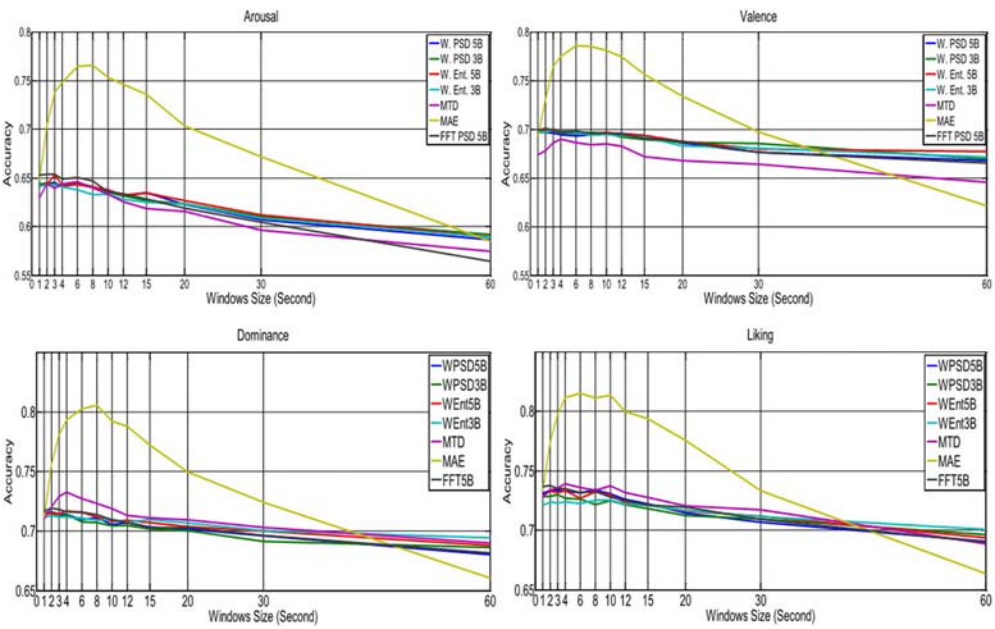

Figure 17.5 Graphical representation of classification results for four emotions planes with seven elements. Classification results of four emotions: arousal, valence, dominance, liking.

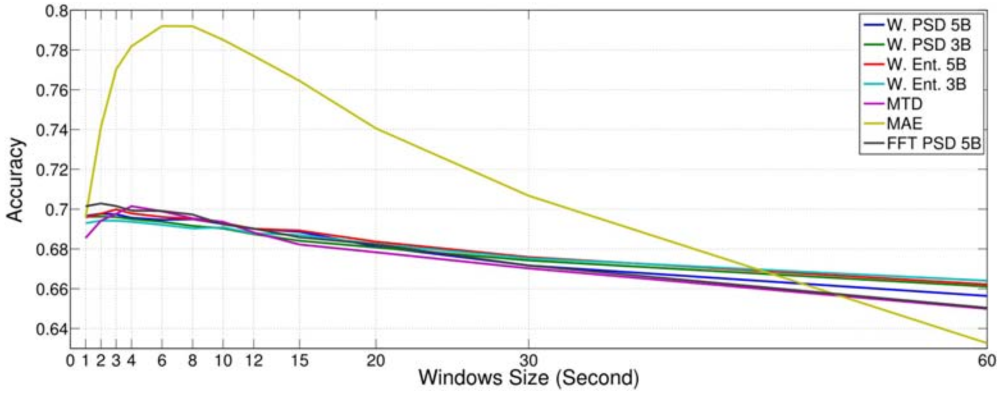

Figure 17.6 Graphical representations of four emotions' weighted average accuracy for seven features. Weighted average of seven features.

Table 17.1 The *t*-test of three versus five bands wavelet entropy features for valence emotion, with the hypothesis that "The difference of accuracy between three and five bands entropy features is nonsignificant" as the test's hypothesis (P>.05).

Window (s)	Accuracy three bands (% ± std)	Accuracy five bands (% ± std)	*P*-Value
1	69.7 ± 0.3	69.8 ± 0.2	.93
2	69.7 ± 0.4	± 69.9 ± 0.3	.61
3	69.7 ± 0.5	70.0 ± 0.3	.14
4	69.8 ± 0.6	69.8 ± 0.4	.50
6	69.7 ± 0.8	69.8 ± 0.9	.33
8	69.4 ± 0.8	69.6 ± 0.6	.24
10	69.5 ± 0.9	69.7 ± 0.8	.19
12	69.3 ± 0.8	69.5 ± 1.1	.22
15	69.2 ± 1.1	69.4 ± 1.1	.27
20	69.3 ± 1.3	68.8 ± 1.3	.95
30	68.1 ± 1.7	68.0 ± 1.5	.59
60	67.1 ± 3.0	67.7 ± 1.8	.18

unassuming window. The significant ascent began at the 12- to 3-s window and then retreated. Additionally, the maximum level of precision is 70%.

The analysis is carried on by contrasting the classification outcomes of five and three bands wavelet entropy, as depicted in Fig. 17.6, because wavelet entropy is more accurate than wavelet PSD features. The graphs show that the features have slightly different accuracy. Between 12- and 3-s windows, both features maintain significantly increased accuracy.

A *t*-test was used to test the hypothesis that "The difference of accuracy between three and five bands entropy features is nonsignificant" and to determine the significance of the accuracy difference between three and five bands wavelet entropy. Table 17.1

depicts the outcome of valence emotion. All window sizes have *P*-values greater than 0.05, indicating that the difference is insignificant, as shown in the table. The *P*-values for the three other emotions are consistent, showing no significant difference.

17.4.4 Analysis of MAE compared to other features

The next step in the analysis is to compare the classification results using MAE, MTD, wavelet entropy, and FFT PSD features. Fig. 17.6 shows this comparison in greater detail. The graphs demonstrate that MAE performs better than these other features. Contrasted with different elements, the precision of MAE leads by roughly 10% at the greatest. The *MAE* accuracy reaches its highest point at 79.2%. Taking the *t*-test with the hypothesis that "The difference of accuracy between *MAE* and *FFT PSD* features is significant," as shown in Table 17.2 for the liking emotion, we also provide the comparison between *MAE* and *FFT PSD* as our comparative study to other features to complete the analysis. The difference is significant across all four emotional planes.

17.4.5 Analysis of testing and training time for seven features

Additional data about the handling time for both preparation and testing for every one of the seven highlights utilizing the SVM classifier are given in Fig. 17.7. The weighted average of the training and testing times for four emotional planes and seven features is used to create the graphs. The preparation and testing time for each of the seven elements likewise demonstrate a comparative pattern. According to the graphs, the EEG-emotion signal only needs less than 100 s to train with a window size of 4 s or more oversized. However, the training time significantly increases from the 3-s

Table 17.2 The *t*-test comparing mean wavelet approximation coefficients with wavelet entropy (MAE) and fast Fourier transform (FFT) power spectral density (PSD) features for liking emotion, hypothesizing that "The difference of accuracy between MAE and FFT PSD features is significant" ($P < .05$).

Window (s)	Accuracy FFT PSD (% ± std)	Accuracy MAE (% ± std)	*P*-Value
1	73.7 ± 0.2	73.3 ± 0.2	3.17 e − 8
2	73.8 ± 0.4	77.4 ± 0.4	4.43 e − 26
3	73.5 ± 0.6	79.8 ± 0.5	1.73 e − 28
4s	73.5 ± 0.5	81.2 ± 0.7	9.25 e − 32
6	73.2 ± 0.7	81.5 ± 0.7	1.21 e − 28
8	73.3 ± 0.7	81.1 ± 1.1	1.47 e − 24
10	72.8 ± 1.1	81.4 ± 1.4	6.22 e − 22
12	72.5 ± 1.1	80.0 ± 1.2	1.09 e − 20
15	72.2 ± 1.1	79.4 ± 1.6	5.32 e − 22
20	72.0 ± 0.9	77.6 ± 1.6	3.83 e − 24
30	70.9 ± 1.5	73.4 ± 2.0	9.90 e − 08
60	69.0 ± 2.8	66.4 ± 2.7	1.00 e − 3

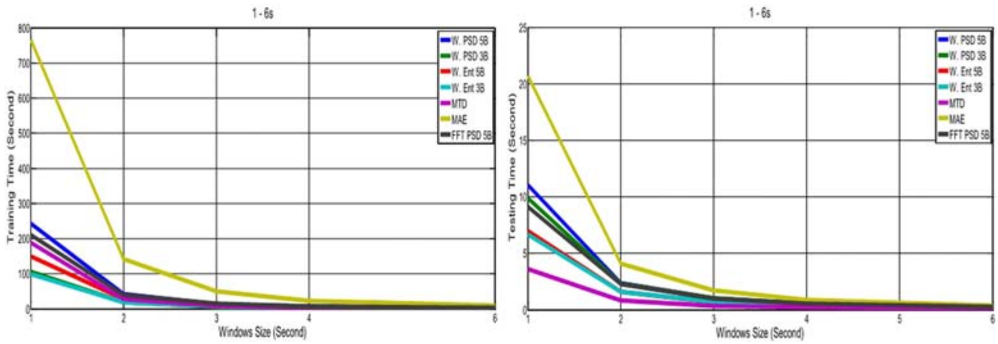

Figure 17.7 Weighted average of optimal training and testing time for four planes of emotions of EEG-emotion signal classification using seven features. *Left*: training time. *Right*: testing time. *EEG*, Electroencephalography.

window to the lower. The pattern of time spent on the test is similar to that of the training time, but the actual time spent is not precisely the same as the training time. The duration of the training and testing will be reduced by accommodating a 4-s window or higher when this event is considered.

17.4.6 Proposed optimal window selection in electroencephalography-emotion classification of seven features for all emotions

After analyzing the weighted average accuracy and the training and testing times for all features, we created a color graph image and gave it a name. Fig. 17.8 depicts the variety chart for OWS. For each of the seven highlights, the OWS variety chart addresses the weighted standard exactness of four planes of emotions. This OWS color graph has three main areas. These three areas can be used to determine the best window: the first region between 60 and 15 s has the lowest classification results, with slightly faster training and testing times. The second area between 12 and 4 s holds the most high-request results with more restricted readiness and testing time.

This region's classification results can be improved by 3%−15% using any of the features compared to the lowest region. There is a lengthy training and testing delay in the third region between 3 and 1 s, even though some features may provide slightly higher accuracy. Therefore, our recommendation for OWS in EEG-emotion classification is the second region enclosed in the green dotted box. We can achieve the highest classification scores in this region while reducing the time spent training and testing for all seven features. With an accuracy of up to 80% in the 6-s window, the MAE also has the best classification results among other features in this area.

Figure 17.8 OWS color graph. The numbers in the graph depict the weighted average accuracy of four emotion planes for every seven features. For each of the seven features, the color heatmap displays various levels of accuracy yielded by window size between 1 and 60 s, with darker colors indicating higher accuracy. The best window can be found by looking at the graph. *OWS*, Optimal window selection.

17.5 Conclusion

In light of the effects of the COVID-19 pandemic, it is essential to develop emotion detection and recognition techniques to address emerging mental health issues.

Examination of OWS in the order of EEG-emotion signal was performed utilizing an SVM. The features were wavelet PSD, wavelet entropy, naive MTD, and the combination of MAE. The examination uncovers that wavelet PSD and wavelet entropy highlights give equivalent outcomes. Only three of the five bands available can be used to reduce frequency bands, resulting in identical results for both wavelet features.

The optimal window can be identified with the help of the OWS color graph. The OWS variety diagram recommends that the ideal window be somewhere between 4 and 12 s. Depending on the features used, an increase in accuracy of 3%–15% can be achieved in this region. Additionally, the time required for training and testing can be reduced within the region. This ideal window can be used for all four emotional planes: dominance, arousal, valence, and liking.

The proposed MAE feature also performs better when compared to other features using FFT PSD.

In particular, the benefit of OWS is that it replicates the pseudostationary signal within the chosen optimal window, which has a desirable statistical property. Regardless of the features used, this statistical property improves classification accuracy.

Further work examples include applying dimensional reduction to MAE features and exploring the OWS with additional classifiers and a deep belief network for optimization.

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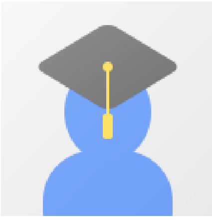

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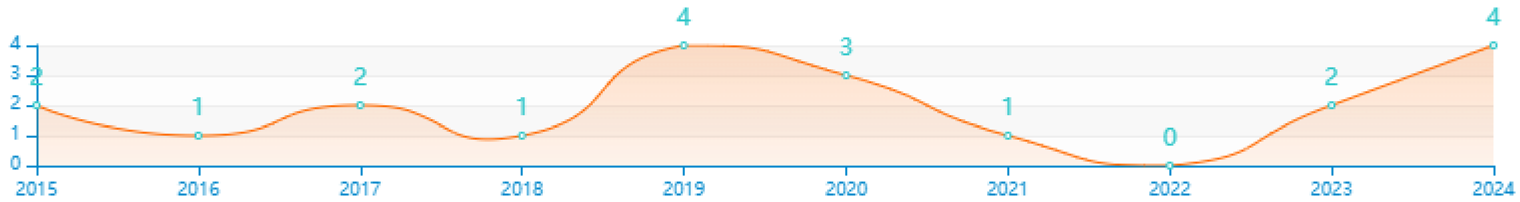

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