Signal Processing and Renewable Energy
September 2024, (pp. 63-71)
ISSN: 2588-7327
eISSN: 2588-7335

Emotion Classification Using EEG Signals and Machine Learning Methods

Mehrnoosh Rezayati[1], Mohammad Adeli*[1]

[1] Department of Biomedical Engineering, Dezful Branch, Islamic Azad University, Dezful, Iran.

Received: 20-Jun-2024, Revised: 26-Aug-2024, Accepted: 27-Aug-2024.

Abstract

This paper presents a method of emotion classification from EEG signals. This method comprises four steps of pre-processing by low-pass filtering, feature extraction using the discrete wavelet transform and the Wigner–Ville distribution, dimensionality reduction using linear discriminant analysis, and classification. The k-nearest neighbors, random forests, and support vector machines were used as classification models. The results of this study showed that the features extracted by the wavelet transform and Wigner–Ville distribution led to the improvement of classification accuracy compared to other studies. In addition, the highest accuracy of 94.1% for the classification of 4 emotions was obtained using the features of the TP9 electrode and the support vector machine classifier.

Keywords: EEG, Emotion Classification, Machine Learning, Feature Extraction, Wavelet.

1. INTRODUCTION

Emotion classification using electroencephalography (EEG) is a fascinating field that has the potential to revolutionize the understanding and interpretation of human emotions. EEG is a non-invasive technique for recording the electrical activity of the brain. By analyzing the patterns of this electrical activity, researchers are able to classify different emotions and gain valuable insights into the functions of the human brain [1]. Objective evaluation and classification of our emotions are fascinating and pave the way for studying and understanding the complexities of human emotions. The potential applications of emotion classification using EEG are truly exciting [2]. For instance, emotion detection using machine learning could contribute to the understanding of mental health disorders such as anxiety and depression [3]. By analyzing the EEG patterns associated with

***Corresponding Authors Email:** mohammad.adeli@iau.ac.ir

different emotional states, researchers could identify specific biomarkers that could aid in the diagnosis and treatment of these disorders [4]. This could lead to more personalized and effective interventions, ultimately improving the lives of millions of people. Brain-computer interface is another field in which emotion classification using EEG can assist [5]. For example, a smart application could detect when a user is feeling stressed or frustrated and respond by providing calming music or suggesting relaxation techniques [6]. This could greatly enhance the user experience and make technology more intuitive and responsive to our emotional needs. Furthermore, emotion classification using EEG has the potential to play a key role in the market research and advertising industry [7]. Companies could gain important information about what appeals to their target audience through the measurement of consumer's emotions in relation to various advertisements and products [8]. This could help them find more effective marketing strategies to increase sales. Additionally, it could help to identify potential issues or concerns with previous products, allowing companies to make necessary adjustments before re-launching them into the market. Emotion classification using machine learning has gained a lot of popularity in recent years [9-11]. Liu et al. (2018) classified emotion for Arousal-Valence recognition using EEG signals. This study reported that a combination of supervised and unsupervised feature dimensionality reduction methods can improve the performance of the classification model [12]. Acharya et al. (2020) reported an accuracy of 88.6 % for emotion [13]. The method proposed by Ghosh et al. (2021) obtained accuracies of 82% and 72% in a binary and a three-class emotion classification problem, respectively [14].

The rest of this paper is organized as follows: Section 2 introduces the EEG dataset and describes the proposed method including preprocessing, feature extraction, and classification. Section 3 describes the results and findings of the study. Results are discussed and compared to other studies in Section 4 and final conclusions are presented in Section 5.

2. MATERIALS AND METHODS

2.1. EEG dataset for emotions

The EEG dataset that we used for emotion classification was collected by Suhaimi et al. (2022) [15]. First, they manually selected 39 primary video stimuli with a virtual reality device that elicited the most effective emotional responses. Second, these initial video stimuli were evaluated by structurally placing each of corresponding videos into a quadrant of arousal-valence space model. Fig. 1 shows arousal-valence space model

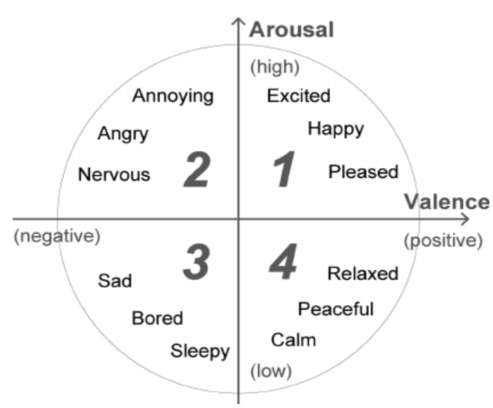

Fig. 1. Arousal-Valence model.

collected EEG signals were collected from four different channels (AF7, AF8, TP9, TP10) with the F_{pz} being the reference. The 50 Hz power line interference was removed using a notch filter. EEG signals were recorded at 0.5 s intervals by Muse Monitor at an initial sampling rate of 256 Hz with four-channel electrodes placed at AF7, AF8, TP9, and TP10.

2.2. Preprocessing

In [16], it was proposed to use frequencies from 0 to 45 Hz for emotion detection. Therefore, we used a low-pass Butterworth filter to remove frequencies above 45 Hz. The magnitude frequency response of this filter is given by Eq. (1):

$$|H(f)|^2 = \frac{1}{1 + (\frac{f}{f_c})^{2N}} \tag{1}$$

where f_c is cut-off frequency (45 Hz) and N, the order of the filter, is 8.

2.3. Feature Extraction

In this study, feature extraction was performed using the discrete wavelet transform and the Wigner-Ville distribution function.

2.3.1. Wavelet Transforms

Wavelet transform (WT) is a time-frequency domain analysis and wavelet functions are derived from a mother wavelet [17]. The continuous wavelet transform of a signal is defined as the inner product of the signal and translated and scaled versions of the mother wavelet according to Eq. (2) and Eq. (3).

$$C_x(a,b) = \int_{-\infty}^{+\infty} x(t)\psi_{a,b}^*(t)dt \tag{2}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \quad a,b \in R \tag{3}$$

In Eq. (2) and (3), a and b are the scale and translation parameters, respectively, C_x denotes the wavelet coefficients, and $\psi(t)$ is the mother wavelet. In the discrete wavelet transform, signals are divided into two components using a low-pass and a high-pass filter. Then, the low-pass component is further split into two components. This could be repeated as long as needed. In this study, variance, signal wavelength, and entropy of wavelet coefficients were estimated and used as features. After 4 levels of decomposition, five signal components (1 approximation, and 4 details) are obtained. We estimated 3 features for each component, resulting in $5 \times 3 = 15$ features. Since these five components are zero-mean signals, their variances are equivalent to their powers, therefore providing a representation similar to the power spectrum, which is commonly used in EEG processing applications [18]. Since entropy is a measure of randomness, that is why we used it.. Unlike variance, entropy is considered a non-linear feature which has also been used in EEG processing applications [18].

2.3.2. Wigner-Ville distribution

Wigner-Ville distribution was first proposed by Wigner in 1932 [19]. It is a suitable transform for time-frequency analysis. This approach has more resolution compared to the short-time Fourier transform. Wigner-

Ville distribution $W_x(t,v)$ is given by Eq. (4):

$$W_x(t,v) = \int_{-\infty}^{+\infty} x\left(t+\frac{\tau}{2}\right) x^*(t - \frac{\tau}{2}) e^{-j2\pi v\tau} d\tau \quad (4)$$

where t and v are time and frequency, respectively. In the end, 3 features including variance, mean, and signal wavelength are calculated from the Wigner-Ville distribution. If $\{|W_x(t,v_i)|, \quad i = 1,2,3\}$ are the three frequency components of the absolute Wigner-Ville distribution $|W_x(t,v)|$ that have the highest power, the mean, variance and the wavelength of these three components are estimated. The respective features are then averaged, resulting in 3 features: an average mean, an average variance, and an average wavelength. The three averages were used as features.

2.4. Classification

Before classification, linear discriminant analysis (LDA) was used for dimensionality reduction. LDA finds linear combinations of features that best discriminate two or more classes of objects or individuals [20]. It is based on the assumption that the conditional probability density functions $p(X\,|Y=0)$ and $p(X\,|Y=1)$ both have normal distributions. The linear discriminator is found using the maximum likelihood discriminant rule from Eq. (5) [20].

$$P(Y=k|X) = \frac{P(X|Y=k)P(Y=k)}{\sum P(X|Y=j)P(Y=j)} \quad (5)$$

In Eq. (5), Y is the class index and X is the feature vector. Details of dimensionality reduction using LDA can be found in [21].

Using LDA, the features were reduced from 18 (15 extracted by discrete wavelet, and the other 3 by Wigner-Ville distribution) to 3.

In this study, three classification methods of k-nearest neighbor (kNN), support vector machine (SVM), and random forest (RF) were used to classify four emotions of happiness, scaredness, calmness, and boredom. The kNN was implemented by setting the parameter $k = 3$ and RF was performed using 25 decision trees for calculations related to the algorithm.

The EEG signals were randomly divided into a training (80%) and a test (20%) set. The three classifiers (SVM, kNN, and RF) were trained on the training data and then evaluated on the test data.

2.4.1. Evaluation of the classifiers' performance

Three metrics were used for the evaluation of the classifiers: accuracy (A_c), precision (P_r), and recall (R_e). These metrics are defined as:

$$Ac = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

$$P_r = \frac{TP}{TP+FP} \quad (7)$$

$$R_e = \frac{TP}{TP+FN} \quad (8)$$

In Eqs. (6-8), TP is the number of patients correctly classified as patients, FN is the number of patients wrongly classified as healthy subjects, TN is the number of healthy subjects correctly classified as healthy, and FP is the number of healthy subjects wrongly classified as patients. Multi-class versions of accuracy, precision, and recall are defined in [22].

3. RESULTS

Table 1 demonstrates the accuracy, precision, and recall of test data of each electrode using the SVM model. RF algorithm was also considered with 25 decision trees, which had the best performance (Table 2). The kNN algorithm was also considered with $k = 3$, which had the best performance (Table 3).

The accuracy of the three classification models, i.e. SVM, kNN, and RF, are briefly compared in Fig. 2. The SVM model and TP9 electrode had the best performance among all the three algorithms and recording electrodes.

Table 1. ***Accuracy, precision, and recall for the SVM classifier.***

Electrode	Accuracy	Precision	Recall
AF8	0.85	0.86	0.88
AF7	0.78	0.77	0.79
TP9	0.94	0.95	0.91
TP10	0.85	0.88	0.87

Table 2. ***Accuracy, precision, and recall for the RF classifier.***

Electrode	Accuracy	Precision	Recall
AF8	0.85	0.88	0.89
AF7	0.76	0.80	0.76
TP9	0.91	0.89	0.90
TP10	0.85	0.86	0.87

Table 3. ***Accuracy, precision, and recall for the kNN algorithm with $k = 3$.***

Electrode	Accuracy	Precision	Recall
AF8	0.83	0.85	0.84
AF7	0.71	0.72	0.73
TP9	0.85	0.88	0.85
TP10	0.81	0.85	0.82

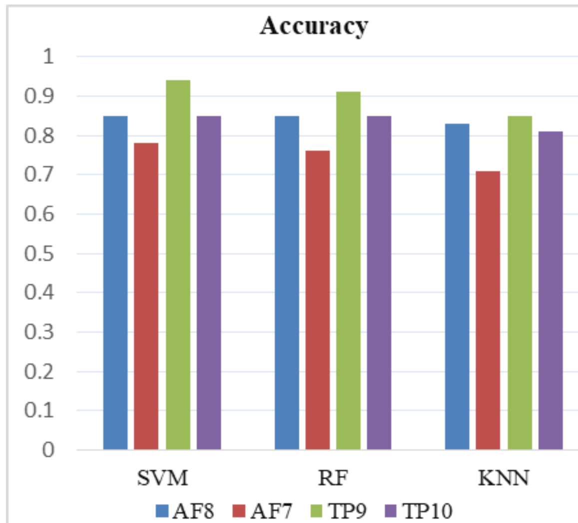

Fig. 2. Classification accuracy of the SVM, RF, and kNN algorithms for AF8, AF7, TP9 and TP10 electrodes.

Table 4. ***The obtained accuracies for three combinations of electrodes.***

Classifier	AF7-AF8	TP9-TP10	AF7-AF8-TP9-TP10
kNN	0.76	0.78	0.71
SVM	0.86	0.86	0.82
RF	0.84	0.85	0.81

The electrode combinations AF7-AF8, TP9-TP10, and AF7-AF8-TP9-TP10 (all electrodes) were also investigated. The results are summarized in Table 4.

4. DISCUSSION

This research investigated three non-linear classification methods (i.e. SVM, kNN, and RF) to recognize four emotions of scaredness, happiness, calmness, and boredom. The SVM $(Ac = 0.94)$ outperformed both the RF $(Ac = 0.91)$ and the kNN $(Ac = 0.85)$. These results are consistent with the results reported in many other EEG processing applications [18], yet it might not be reasonable to generalize these results especially. In some studies on emotion recognition from EEG, kNN was reported to be the best classifier [18]. Therefore, more studies should be conducted to investigate the classification models using other feature types, feature selection or dimensionality reduction algorithms, and other datasets of emotion recognition.

Classification accuracy has been limited in many studies. For example, Gannouni et al. (2021) [23] obtained an accuracy of 89% for a four-class emotion recognition problem, which is lower than the accuracy we obtained (94%) using SVM. Sengur and Siuly (2020) [24] obtained a high accuracy of 94% which is comparable to the result we obtained. However, they had two classes of emotions while we used four classes of emotions. Our approach was also better than that of Subasi et al. (2021) [25] which gained an accuracy of 93% for a three-class classification problem. Housein et al. (2022) [26] conducted a review study on the classification of emotions based on the brain-computer interface and mentioned classification accuracy of machine learning methods varies from 61.17% to 93% in studies (Table 5). Therefore, this study seems to have a better performance compared to other studies. The machine learning models we used are not different from those used in other studies. Therefore, it seems that the combination of the time-frequency features extracted from the wavelet coefficients and the Wigner-Ville distribution provided an effective set of features for emotion classification.

It should be noted that the current study has a few limitations. First, the dataset that we used in this study included EEG data from only 4 recording channels. Therefore, it is necessary to evaluate the proposed method on other datasets with more recording channels. Another constraint of this study is the limited set of features we used. Features such as time-domain features could also be tested in future studies. Also, other feature

Table 5. ***Comparison of the results of this study with similar studies.***

References	Methods	Emotions	Accuracy
[27]	DT, kNN, RF	Positive, negative and neutral	74 %
[28]	LDA	Positive, negative and angry and harmony	82 %
[29]	SVM	Positive, negative and neutral	85.9 %
[30]	RF	Happy, sad, angry, calm	75.6 %
Present study	kNN, RF, SVM	Happy, scared, bored, calm	94.1 %

selection or dimensionality reduction techniques should be considered. In addition, linear and other non-linear machine learning models and deep learning-based models can be used to find the best classifier for emotion recognition.

5. CONCLUSION

In this study, classification of four emotions (i.e. happiness, calmness, boredom, and scaredness) was successfully performed using the SVM classifier and the features from the TP9 electrode. This achievement is due to the effective features that the discrete wavelet transform and the Wigner-Ville distribution provide. In future studies, other feature extraction and classification methods should be investigated for emotion classification.

REFERENCES

[1] Wang, J. and M. Wang, Review of the emotional feature extraction and classification using EEG signals. Cognitive robotics, 2021. 1: p. 29-40.

[2] Suhaimi, N.S., J. Mountstephens, and J. Teo, EEG-based emotion recognition: A state-of-the-art review of current trends and opportunities. Computational intelligence and neuroscience, 2020. 2020.

[3] Chang, H., Y. Zong, W. Zheng, C. Tang, J. Zhu, and X. Li, Depression assessment method: an eeg emotion recognition framework based on spatiotemporal neural network. Frontiers in Psychiatry, 2022. 12: p. 837149.

[4] Dev, A., N. Roy, M.K. Islam, C. Biswas, H.U. Ahmed, M.A. Amin, F. Sarker, R. Vaidyanathan, and K.A. Mamun, Exploration of EEG-based depression biomarkers identification techniques and their applications: a systematic review. IEEE Access, 2022. 10: p. 16756-16781.

[5] Kaur, B., D. Singh, and P.P. Roy, EEG based emotion classification mechanism in BCI. Procedia computer science, 2018. 132: p. 752-758.

[6] Al-Nafjan, A., M. Hosny, Y. Al-Ohali, and A. Al-Wabil, Review and classification of emotion recognition based on EEG brain-computer interface system research: a systematic review. Applied Sciences, 2017. 7(12): p. 1239.

[7] Pei, G. and T. Li, A literature review of EEG-based affective computing in marketing. Frontiers in Psychology, 2021. 12: p. 602843.

[8] Liu, Y., O. Sourina, and M.R. Hafiyyandi. EEG-based emotion-adaptive advertising. in 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction. 2013. IEEE.

[9] Bălan, O., G. Moise, L. Petrescu, A. Moldoveanu, M. Leordeanu, and F. Moldoveanu, Emotion classification based on biophysical signals and machine learning techniques. Symmetry, 2019. 12(1): p. 21.

[10] Zhang, J., Z. Yin, P. Chen, and S. Nichele, Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. Information Fusion, 2020. 59: p. 103-126.

[11] Domínguez-Jiménez, J.A., K.C. Campo-Landines, J.C. Martínez-Santos, E.J. Delahoz, and S.H. Contreras-Ortiz, A machine learning model for emotion recognition from physiological signals. Biomedical signal processing and control, 2020. 55: p. 101646.

[12] Liu, J., H. Meng, M. Li, F. Zhang, R. Qin, and A. Nandi, Emotion detection from EEG recordings based on supervised and unsupervised dimension reduction. Concurrency and Computation: Practice and Experience, 2018. 30: p. e4446.

[13] Acharya, D., R. Jain, S.S. Panigrahi, R. Sahni, S. Jain, S.P. Deshmukh, and A. Bhardwaj. Multi-class emotion classification using EEG signals. in Advanced Computing: 10th International Conference, IACC 2020, Panaji, Goa, India, December 5–6, 2020, Revised Selected Papers, Part I 10. 2021. Springer.

[14] Ghosh, S.M., S. Bandyopadhyay, and D. Mitra, Nonlinear classification of emotion from EEG signal based on maximized mutual information. Expert Systems with Applications, 2021. 185: p. 115605.

[15] Suhaimi, N.S., J. Mountstephens, and J. Teo, A dataset for emotion recognition using virtual reality and EEG (DER-VREEG): emotional state classification using low-cost wearable VR-EEG headsets. Big Data and Cognitive Computing, 2022. 6(1): p. 16.

[16] Bhardwaj, A., A. Gupta, P. Jain, A. Rani, and J. Yadav. Classification of human emotions from EEG signals using SVM and LDA Classifiers. in 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN). 2015.

[17] Al-Qerem, A., F. Kharbat, S. Nashwan, S. Ashraf, and K. Blaou, General model for best feature extraction of EEG using discrete wavelet transform wavelet family and differential evolution. International Journal of Distributed Sensor Networks, 2020. 16(3): p. 1550147720911009.

[18] Saeidi, M., W. Karwowski, F.V. Farahani, K. Fiok, R. Taiar, P.A. Hancock, and A. Al-Juaid, Neural decoding of EEG signals with machine learning: a systematic review. Brain Sciences, 2021. 11(11): p. 1525.

[19] Alsalmi, H. and Y. Wang, Mask filtering to the Wigner-Ville distribution. Geophysics, 2021. 86(6): p. V489-V496.

[20] Xanthopoulos, P., P.M. Pardalos, T.B. Trafalis, P. Xanthopoulos, P.M. Pardalos, and T.B. Trafalis, Linear discriminant analysis. Robust data mining, 2013: p. 27-33.

[21] Gu, Q., Z. Li, and J. Han. Linear discriminant dimensionality reduction. in Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2011, Athens, Greece, September 5-9, 2011. Proceedings, Part I 11. 2011. Springer.

[22] Sokolova, M. and G. Lapalme, A systematic analysis of performance measures for classification tasks. Information processing & management, 2009. 45(4): p. 427-437.

[23] Gannouni, S., A. Aledaily, K. Belwafi,

and H. Aboalsamh, Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification. Scientific Reports, 2021. 11(1): p. 7071.

[24] Şengür, D. and S. Siuly, Efficient approach for EEG-based emotion recognition. Electronics Letters, 2020. 56(25): p. 1361-1364.

[25] Subasi, A., T. Tuncer, S. Dogan, D. Tanko, and U. Sakoglu, EEG-based emotion recognition using tunable Q wavelet transform and rotation forest ensemble classifier. Biomedical Signal Processing and Control, 2021. 68: p. 102648.

[26] Houssein, E.H., A. Hammad, and A.A. Ali, Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review. Neural Computing and Applications, 2022. 34(15): p. 12527-12557.

[27] Qing, C., R. Qiao, X. Xu, and Y. Cheng, Interpretable emotion recognition using EEG signals. Ieee Access, 2019. 7: p. 94160-94170.

[28] Chakladar, D.D. and S. Chakraborty, EEG based emotion classification using “correlation based subset selection”. Biologically inspired cognitive architectures, 2018. 24: p. 98-106.

[29] Huang, C., Recognition of psychological emotion by EEG features. Network Modeling Analysis in Health Informatics and Bioinformatics, 2021. 10: p. 1-11.

[30] Pane, E.S., A.D. Wibawa, and M.H. Purnomo, Improving the accuracy of EEG emotion recognition by combining valence lateralization and ensemble learning with tuning parameters. Cognitive processing, 2019. 20: p. 405-417.