EEG-Based Emotion Recognition Research Postprint

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Abstract

To address the question of improving the accuracy of EEG-based emotion recognition, after performing frequency-band feature extraction on raw EEG signals, we employed, on the one hand, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, and neural network algorithms for training and classification using features including wavelet entropy, approximate entropy, power spectral density, and differential entropy. On the other hand, based on four different electrode placement configurations, differential entropy features were trained using both standard SVM and a genetic algorithm-parameter-optimized SVM. The results demonstrate that under 12-channel conditions, an overall accuracy of 91.99% can be achieved, with the highest emotion recognition accuracy reaching 97.59%. The findings indicate that reducing the number of electrodes can yield high emotion recognition classification performance, and that employing the parameter-optimized SVM algorithm can effectively enhance accuracy.

Full Text

Abstract

This study addresses the challenge of improving emotion recognition accuracy from EEG signals. Following band-specific feature extraction from raw EEG data, we employed Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes (NB), and Neural Network algorithms to train and classify four feature types: wavelet entropy, approximate entropy, power spectral density, and differential entropy. Additionally, using four distinct electrode montages, we trained differential entropy features with both standard SVM and genetically-optimized SVM. Results demonstrate that a 12-channel configuration achieves 91.99% overall accuracy, with peak emotion recognition rates reaching 97.59%. These findings indicate that reduced electrode montages can yield high classification performance, and that parameter-optimized SVM significantly enhances accuracy.

Keywords: EEG signal; emotion recognition; differential entropy; channel selection; genetic algorithm

0 Introduction

As artificial intelligence advances, enabling computers to emulate human perceptual, cognitive, and behavioral functions has become a focal research area. Affective computing represents a crucial component of intelligent, human-centered human-computer interaction [1]. While researchers such as Anderson and McOwan [2], Ang [3], and others have utilized facial expressions, vocal cues, and gestures for emotion recognition [4], these signals are often easily concealed. Other physiological indicators like heart rate, respiration, and skin temperature suffer from low accuracy, limiting their utility in emotion recognition. Consequently, EEG signals have gained prominence in recent years due to their high classification accuracy.

Hosseini et al. [5] extracted approximate entropy features from EEG signals, achieving 73.25% accuracy using SVM for emotion recognition. Yuen et al. [6] employed six time-domain statistical features with neural networks for classification. Madsen et al. [7] demonstrated the importance of temporal information in emotion representation, while Li [8] proposed a band-search method for selecting optimal frequency bands. Lin et al. from National Taiwan University [9] used SVM to classify emotions into joy, anger, sadness, and pleasure based on EEG signals, identifying 30 emotion-related features and confirming the critical role of frontal and parietal lobes. Valenzi [10] achieved 87.5% accuracy using only eight electrodes (AF3, AF4, F3, F4, F7, F8, T7, T8). Researchers from Beihang University and Tsinghua University have also investigated physiological signals and multimodal emotion analysis.

Despite progress, few studies have explored multi-feature extraction across multiple frequency bands using various classification methods to fully exploit EEG' s intrinsic information. Furthermore, optimal channel and frequency band selection, along with electrode evaluation criteria, remain underexplored. Emotion changes reflect specific brain activities, creating a bidirectional mapping between affective states and neural patterns. EEG serves as the bridge connecting these domains. However, raw EEG signals are massive, weak, and noisy, necessitating feature extraction to represent their essential characteristics.

This study presents a comprehensive analysis of EEG-based emotion recognition, extracting differential entropy (DE), wavelet entropy (WE), approximate entropy (ApEn), and power spectral density (PSD). We employ SVM, KNN, Naive Bayes, multi-layer perceptron (MLP), and genetic algorithm-optimized SVM to identify relevant frequency bands and channels, achieving robust emotion recognition from EEG signals.

1.1 Experimental Setup and Data

Effective emotion elicitation is fundamental to emotion research. Various stimuli exist, including images, music, and films. Compared to alternatives, film clips offer superior engagement through narrative content, visual scenes, and audio, creating more realistic contexts that elicit strong subjective and physiological responses. Therefore, this study utilized film clips as emotional stimuli.

The dataset [11, 12] comprises 15 clips, each approximately 4 minutes long, designed to evoke three emotional categories: positive, neutral, and negative. Physiological signal indicators reflect specific arousal levels and can represent multiple emotional states. While many EEG datasets remain proprietary, this publicly available resource provides a valuable training set for emotion recognition research.

1.2 EEG Emotion Recognition Pipeline

The EEG emotion recognition process follows the workflow shown in Figure 1 [Figure 1: see original paper]. EEG signals were recorded from 62 scalp channels while subjects viewed film clips. To enhance reliability, data from six subjects (15 clips each) were randomly partitioned into training and test sets at a 9:6 ratio. A 1-second window was applied, with all 62 electrodes recording data at 1-second intervals. Features were extracted both with and without frequency band division. Subsequently, classification training was performed across multiple channels, followed by genetic algorithm-based SVM parameter optimization.

2.1 Feature Extraction

Signal detection and classification fundamentally depend on feature extraction. Numerous methods exist for EEG feature extraction, including time-domain [13], frequency-domain [14], time-frequency domain, and nonlinear dynamical features [15]. Given EEG' s complex morphology and lack of standardized analysis methods, we focused on frequency-domain, time-frequency, and nonlinear dynamical features.

The dataset employs three emotion categories, where single features can achieve satisfactory classification. In the frequency domain, we extracted differential entropy and power spectral density. Due to EEG' s high low-frequency energy, differential entropy (DE) [16]—a generalization of Shannon entropy—effectively distinguishes high and low-energy brain patterns by discretizing continuous variables. Power spectral density (PSD) [17] describes power distribution across frequencies, using signal variance for identification.

Time-frequency analysis examines signals in both domains simultaneously, benefiting non-stationary and time-varying signals by highlighting transient characteristics. Short-time Fourier transform has achieved 91.35% accuracy in EEG emotion classification [18]. Wavelet entropy (WE) [19] extends this approach, overcoming fixed-window limitations by adapting to both high and low frequencies for superior classification.

Nonlinear dynamical features capture EEG' s inherent properties, as brain signals emerge from nonlinear neural coupling. Approximate entropy (ApEn) [20] quantifies system randomness by measuring conditional probability of pattern persistence when embedding dimension increases from m to m+1. Higher entropy indicates greater novelty generation in time series.

EEG signals are scientifically categorized into five bands [21]: (1-4 Hz), (4-8 Hz), (8-13 Hz), (13-30 Hz), and (36-44 Hz), as shown in Figure 2 [Figure 2: see original paper]. We extracted DE, WE, ApEn, and PSD features, then applied bandpass filtering to segment them into these five bands.

2.2 Classification Training

Following feature extraction, classification models must be constructed to categorize untrained samples. For our three-class emotion recognition problem, different classifiers yield varying accuracies, demonstrating that recognition performance depends partially on classifier selection.

Multi-Band Training

We employed four classifiers: SVM, KNN, Naive Bayes, and MLP. SVM, a supervised learning model, offers unique advantages for small-sample, nonlinear, and high-dimensional pattern recognition [22]. Its core principle involves nonlinearly mapping training vectors to a high-dimensional space to find an optimal separating hyperplane. Compared to Naive Bayes [23], KNN [24], and MLP [25], SVM avoids neural network structural selection and local minima issues while excelling in high-dimensional problems.

Multi-Channel Training

The 62-channel electrode cap, while comprehensive, generates large data volumes that complicate measurement and analysis. Therefore, we reduced channels using four electrode montages based on the international 10-20 system, as shown in Figure 3 [Figure 3: see original paper]: (a) 4-channel: FT7, FT8, T7, T8; (b) 6-channel: FT7, FT8, T7, T8, TP7, TP8; (c) 9-channel: FP1, PFZ, FP2, FT7, FT8, T7, T8, TP7, TP8; (d) 12-channel: FT7, FT8, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P7, P8.

Channel selection aims to filter electrodes with minimal impact on emotion recognition. Using statistical measures, we leveraged Deep Belief Networks (DBN) for integrated feature extraction and selection during unsupervised and supervised learning. Based on DBN weight coefficients during unsupervised learning, we selected four electrode montages by ranking coefficients from high to low [26].

Parameter Optimization Training

SVM' s kernel functions and parameters significantly affect training outcomes. While empirical parameter selection was initially attempted, we further improved accuracy using genetic algorithms for parameter optimization [27]. Genetic Algorithm (GA), inspired by Darwinian evolution, is a heuristic search method that starts with the fittest individuals in a population, iteratively applying selection, crossover, and mutation to optimize solutions [28]. GA encodes penalty factor c and kernel parameter g in binary, evaluates fitness for elimination while maintaining population size, and outputs optimal c and g values upon meeting termination criteria [29].

3.1 Multi-Band Results

For raw EEG data, we classified DE, WE, ApEn, and PSD features using SVM, KNN, NB, and MLP. SVM employed a linear kernel; KNN used K=20. Table 1 shows WE feature classification accuracy and variance across four classifiers.

Table 1. Mean Classification Accuracy and Standard Deviation for Wavelet Entropy Features

Classifier	Accuracy (SD)
SVM	55.13 (4.05)
KNN	48.72 (2.39)
NB	47.91 (3.05)
MLP	49.49 (3.55)

Table 2 presents ApEn, PSD, and DE features filtered into five bands (Delta, Theta, Alpha, Beta, Gamma) and unsegmented EEG data, trained with four classifiers.

Table 2. Mean Classification Accuracy and Standard Deviation Across Frequency Bands

Feature	Classifier	Delta	Theta	Alpha	Beta	Gamma	Total
ApEn	SVM	43.34 (3.47)	36.08 (2.29)	43.47 (6.28)	42.4 (3.43)	58.66 (5.43)	69.57 (8.33)
ApEn	KNN	34.05 (3.31)	40.51 (1.82)	39.31 (4.06)	39.17 (2.61)	54.6 (6.84)	66.64 (9.84)
ApEn	NB	36.84 (3.09)	39.78 (2.96)	41.93 (5.47)	44.83 (2.57)	52.3 (3.33)	56.36 (7.65)
ApEn	MLP	33.77 (2.63)	36.8 (1.62)	37.36 (5.04)	41.01 (2.12)	55.06 (6.6)	66.73 (9.02)
PSD	SVM	39.52 (4.21)	39.99 (7.49)	45.43 (6.01)	56.81 (12.18)	68.82 (10.73)	80.18 (10.94)

Feature	Classifier	Delta	Theta	Alpha	Beta	Gamma	Total
PSD	KNN	66.32	58.55	62.63	76.52	79.03	85.46
		(4.94)	(5.12)	(9.12)	(4.35)	(4.0)	(3.21)
PSD	NB	38.14	41.39	43.18	46.82	49.08	51.73
		(4.83)	(4.21)	(5.56)	(7.7)	(8.98)	(7.64)
PSD	MLP	47.46	54.61	56.88	67.07	73.03	75.10
		(10.92)	(6.99)	(10.59)	(8.62)	(6.17)	(11.92)
DE	SVM	63.71	61.70	71.35	88.19	93.35	98.45
		(3.42)	(7.38)	(8.97)	(5.37)	(3.74)	(0.82)
DE	KNN	64.03	69.07	77.79	86.86	91.76	93.99
		(3.81)	(7.19)	(9.98)	(5.31)	(2.0)	(2.6)
DE	NB	49.49	46.54	50.73	63.13	67.47	71.22
		(3.66)	(3.11)	(10.01)	(10.9)	(9.36)	(7.86)
DE	MLP	71.96	77.52	82.7	95.4	98.10	98.1
		(5.74)	(8.61)	(8.71)	(3.03)	(0.78)	(0.95)

Results demonstrate that all four classifiers provide valuable references for EEG-based emotion recognition, with SVM consistently outperforming others. Among features, DE yields superior results overall, indicating stronger correlation with human emotions. For wavelet entropy, SVM classification of DE-filtered bands shows significant advantages over total EEG band energy, as illustrated in Figure 4 [Figure 4: see original paper].

3.2 Multi-Channel Results

Based on superior DE feature performance with SVM in multi-band training, we conducted multi-channel classification using the four electrode montages shown in Figure 3 [Figure 3: see original paper]. Table 3 presents accuracy and variance for DE features across different channel configurations.

Table 3. Mean Classification Accuracy and Standard Deviation for Different Electrode Montages

Montage	Delta	Theta	Alpha	Beta	Gamma	Total
4-ch	54.32	55.76	62.91	74.19	81.76	85.46
	(3.38)	(5.13)	(13.49)	(10.23)	(9.89)	(7.03)
6-ch	58.47	59.03	65.47	76.32	84.29	87.91
	(3.41)	(5.51)	(12.81)	(10.35)	(7.81)	(9.22)
9-ch	61.38	63.91	69.84	79.75	87.46	90.13
	(4.74)	(6.28)	(12.16)	(8.49)	(6.22)	(7.79)
12-ch	64.03	66.07	73.51	82.38	89.47	91.99
	(2.78)	(6.39)	(12.74)	(8.83)	(8.19)	(7.52)

Table 3 shows that high classification performance can be achieved even with reduced channels, reaching 91.99% overall accuracy with the 12-channel montage using SVM. This demonstrates that electrode reduction not only reduces computational cost but also improves model performance and robustness.

3.3 Parameter Optimization Results

Based on 12-channel results, we applied gaSVMcgForClass for multiple parameter optimizations on training sets, obtaining average c=1 and g=2. These optimized parameters were used in an RBF-kernel SVM model, yielding improved accuracies [30] shown in Figure 5 [Figure 5: see original paper].

After genetic algorithm optimization, accuracy improved across all frequency bands, with overall accuracy increasing by approximately 5.6% in the 12-channel configuration. The results indicate that higher frequency bands consistently yield better recognition rates, with Gamma band showing superior performance. Overall classification accuracy trends better than individual bands, as higher bands contain more information. Positive emotions exhibit greater and band energy, while neutral and negative emotions show lower energy in these bands.

4 Conclusion

Emotion recognition via computer analysis of characteristic emotional states represents a critical research frontier. This study investigated multi-channel EEG-based emotion recognition, extracting DE, WE, ApEn, and PSD features to evaluate their correlation with emotional states. We trained these features using SVM, KNN, Naive Bayes, and neural networks. Building on SVM's strong performance with DE features, we reduced electrode montages and applied genetic algorithm parameter optimization.

Experimental results demonstrate that: (1) overall subject accuracy exceeds individual band accuracy; (2) recognition accuracy increases with frequency band; (3) DE features outperform other features; and (4) high accuracy can be achieved with fewer channels. These findings partially reflect that high-frequency bands play more important roles in emotional activity than low-frequency bands.

References

[1] Li Wu, Zhang Yanhui, Fu Yingzi. Speech emotion recognition in E-learning system based on affective computing [C]// Proc of the 3rd Conference on Natural Computation. 2007: 809-813.

[2] Anderson A K, Sobel N. Dissociating intensity from valence as sensory inputs to emotion [J]. Neuron, 2003, 39 (4): 581-583.

[3] Ang J, Dhillon R, Krupski A, et al. Prosody-based automatic detection of annoyance and frustration in human-computer dialog [C]// Proc of the 8th International Conference on Spoken Language Processing. 2002: 2037-2040.

[4] Bos D O. EEG-based emotion recognition [EB/OL]. 2008. https://pdfs.semanticscholar.org/5097/b37a30b8d

[5] Hosseini S A, Naghibi-Sistani M B. Emotion recognition method using entropy analysis of EEG signals [J]. International Journal of Image, Graphics and Signal Processing, 2011, 3 (5): 30-36.

[6] Yuen C T, Woo S S, Tan C S, et al. Classification of human emotions from EEG signals using statistical features and neural network [J]. International Journal of Integrated Engineering, 2009, 1 (3): 71-79.

[7] Madsen J, Jensen B S, Larsen J. Modeling temporal structure in music for emotion prediction using pairwise comparisons [C]// Proc of the 15th International Society for Music Information Retrieval Conference. 2014: 73-78.

[8] Li Mi, Lu Baoliang. Emotion classification based on gamma-band EEG [C]// Proc of IEEE International Conference Engineering in Medicine and Biology Society. 2009: 1223–1226.

[9] Lin Yuanping, Wang Chihong, Tzyy Ping Jung, et al. EEG-based emotion recognition in music listening [J]. IEEE Trans on Biomedical Engineering, 2010, 57 (7): 1798-1806.

[10] Mallat S G. A theory for multiresolution signal decomposition: the wavelet representation [J]. IEEE Journals & Magazines, 1989, 11 (7): 674-693.

[11] Zheng Weilong, Zhu Jiayi, Peng Yong, et al. EEG-based emotion classification using deep belief networks [C]// Proc of IEEE International Conference on Multimedia and Expo. 2014: 1-6.

[12] Zheng Weilong, Guo Haotian, Lu Baoliang. Revealing critical channels and frequency bands for emotion recognition from EEG with deep belief network [C]// Proc of International IEEE//EMBS Conference on Neural Engineering. 2015: 154-157.

[13] George Zouridakis, Udit Patidar, Nikhil S. Padhye, et al. Spectral power of brain activity associated with emotion —a pilot MEG study [C]// Proc of the 17th International Conference on Biomagnetism Advances Biomagnetism. Berlin: Springer, 2010: 354-357.

[14] Zhang Qing, Lee Minho. A hierarchical positive and negative emotion understanding system based on integrated analysis of visual and brain signals [J]. Neurocomputing, 2010, 73 (16-18): 3264–3272.

[15] Aftanas L I, Lotova N V, Koshkarov V I, et al. Non-linear analysis of emotion EEG: calculation of Kolmogorov entropy and the principal Lyapunov exponent [J]. Neuroscience Letters, 1997, 226 (1): 13.

[16] Shi Lichen, Jiao Yingying, Lu Baoliang. Differential entropy feature for EEG-based vigilance estimation [C]// Proc of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. 2013: 6627-6630.

[17] Daniela S, Maren G, Thomas F, et al. Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music [J]. Psy-

chophysiology, 2007, 44 (2): 293-304.

[18] Wu Naiyu. EEG-based emotion classification research [D]. Beijing: Minzu University of China, 2013.

[19] Murugappan M, Mohamed R, Ramachandran N, et al. EEG feature extraction for classifying emotions using FCM and FKM [C]// Proc of Wseas International Conference on Applied Computer and Applied Computational Science. World Scientific and Engineering Academy and Society, 2008: 299-304.

[20] Steve P. Approximate entropy (ApEn) as a complexity measure [J]. Chaos An Interdisciplinary Journal of Nonlinear Science, 1995, 5 (1): 110.

[21] Saeid S, Chambers J A. EEG signal processing [M]// The Fernow Watershed Acidification Study. Netherlands: Springer, 2007: 207-236.

[22] Vapnik V N. Statistical learning theory [J]. Encyclopedia of the Sciences of Learning, 2008, 41 (4): 3185-3185.

[23] Deng Weibin, Wang Guoyin, Wang Yan. Weighted naive Bayes classification algorithm based on rough set [J]. Computer Science, 2007, 34 (2): 204-206.

[24] Jiang Tao, Chen Xiaoli, Zhang Yufang, et al. Improved KNN using clustering algorithm [J]. Computer Engineering and Applications, 2009, 45 (7): 153-155.

[25] Hu Jinbin, Tang Xuqing. BP algorithm and its application in artificial neural network [J]. Information Technology, 2004 (4): 1-4.

[26] Zheng Weilong, Lu Baoliang. Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks [J]. IEEE Trans on Autonomous Mental Development, 2015, 7 (3): 162-175.

[27] Zheng Chunhong, Jiao Licheng. Automatic parameters selection for SVM based on GA [C]// Proc of the 5th World Congress Intelligent Control and Automation, 2004: 1876-1879.

[28] Liu Hao, Qiu Jianxin. Improved adaptive genetic algorithm in optimal layout of leather rectangular parts [J]. Advances in Natural Science, 2015, 8 (3): 20-26.

[29] Lalit Mohan Saini, Sahil Kumar Aggarwal, Kumar Atul. Parameter optimisation using genetic algorithm for support vector machine-based price-forecasting model in National electricity market [J]. IET Generation Transmission & Distribution, 2009; 4 (1): 36-49.

[30] Ren Hao, Ye Liang, Li Yue, et al. A speech emotion recognition algorithm based on multi-layer SVM classification [J]. Application Research of Computers, 2017, 34 (6): 1-4.

Note: Figure translations are in progress. See original paper for figures.