Postprint of EEG Emotion Recognition Based on Piecewise Composite Multiscale Fuzzy Entropy and IGWO-SVM

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Abstract

EEG emotion recognition plays an important role in auxiliary lie detection, clinical medicine, and human-computer interaction. To improve the emotion recognition rate of EEG, a segmented composite multiscale fuzzy entropy algorithm is proposed, which employs strategies of segmented coarse-graining and computing composite multiscale fuzzy entropy, enabling the extracted features to better address issues of missing data and computational inaccuracy; simultaneously, a classification model is constructed that applies the grey wolf algorithm with cosine nonlinear convergence factor and dynamic-static position updating to optimize the support vector machine. To verify the effectiveness of the two proposed algorithms, simulation experiments were conducted, and the EEG emotion recognition rates were compared with several common support vector machine optimization models under the public DEAP database, with results showing that under the proposed model, the average recognition rates for valence, arousal, dominance, and liking are 87.27%, 87.81%, 89.06%, and 87.58% respectively, all higher than other algorithms. Additionally, the classification of valence and arousal under high/low liking was compared, and the experiments demonstrate that emotion recognition rates are higher when liking is low.

Full Text

Preamble

EEG Emotion Recognition Based on Piecewise Complex Multi-Scale Fuzzy Entropy and IGWO-SVM Algorithm

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Abstract: EEG-based emotion recognition plays a vital role in auxiliary lie detection, clinical medicine, and human-computer interaction. To improve the recognition accuracy of EEG emotions, this paper proposes a piecewise complex multi-scale fuzzy entropy algorithm that employs piecewise coarse-graining and composite multi-scale fuzzy entropy calculation strategies, enabling the extracted features to better address issues of data loss and computational inaccuracy. Simultaneously, we construct a classification model that uses an improved grey wolf optimizer to optimize support vector machine parameters, incorporating a cosine nonlinear convergence factor and dynamic-static position update strategies. To validate the effectiveness of the proposed algorithms, simulation experiments were conducted, and EEG emotion recognition rates were compared with several common SVM optimization models using the public DEAP database. Results demonstrate that under the proposed model, the average recognition rates for valence, arousal, dominance, and liking reach 87.27%, 87.81%, 89.06%, and 87.58% respectively, all surpassing other algorithms. Additionally, classification of valence and arousal under high/low liking conditions was compared, revealing that emotion recognition rates are higher when liking is low.

Keywords: EEG signals; emotion recognition; improved grey wolf optimizer algorithm; SVM optimization algorithm; piecewise complex multi-scale fuzzy entropy

0 Introduction

Emotion recognition involves analyzing and processing signals acquired from sensors to determine the emotional state of the subject. Among various physiological indicators, methods based on physiological signals are more difficult to disguise than facial expressions, body posture, or vocal intonation, while providing richer information. EEG-based emotion recognition has been widely applied in auxiliary lie detection [1], psychological disease identification [2], and human-computer interaction with Parkinson' s patients [3]. In recent years, nonlinear dynamics-based feature extraction methods have achieved promising results in EEG and other physiological signal research, including fractal dimension [4], permutation entropy [5], spectral entropy [6], approximate entropy [7], and sample entropy [8]. In 2007, Chen et al. developed fuzzy entropy [9] as an improved version of sample entropy—a novel sequence complexity measurement method successfully applied to surface EMG signal feature extraction and classification. Drawing upon the multi-scale fuzzy entropy (MSFE) algorithm proposed by Zou et al. [10], this paper constructs a piecewise complex multi-scale fuzzy entropy (PCMSFE) algorithm for EEG signal features, employing piecewise coarse-graining and composite multi-scale fuzzy entropy computation strategies.

Support vector machine (SVM) is the most widely used method for EEG signal emotion classification, capable of addressing small-sample, nonlinear problems and playing a crucial role in high-dimensional pattern recognition. However, SVM classification performance is significantly influenced by its internal parameters [11]. Consequently, many researchers have applied algorithms such as cuckoo search (CS) [12], particle swarm optimization (PSO) [13], genetic algorithm (GA) [14], and differential evolution (DE) [15] to SVM parameter optimization, though these approaches still exhibit adaptability limitations. Mirjalili et al. [16] created the grey wolf optimizer (GWO), which offers advantages of simple principle, few adjustable parameters, and easy implementation. Nevertheless, GWO suffers from premature convergence, susceptibility to local optima, and dependence on initial population. To address these issues, Zhu et al. [17] proposed a hybrid algorithm combining DE and GWO, though this fusion leads to an overly complex system with suboptimal optimization results. Saremi [18] applied dynamic evolutionary population strategies to GWO to enhance its global search capability. Therefore, this paper develops an improved GWO (IGWO) based on a cosine nonlinear convergence factor and dynamic-static position updates to balance local and global search capabilities.

This paper focuses on feature extraction and classification problems in EEG emotion recognition, with contributions as follows: (a) To prevent data loss and inaccurate entropy calculation, we propose a multi-scale fuzzy entropy algorithm using piecewise coarse-graining and composite entropy calculation. Simulation tests on white noise and 1/f noise, along with EEG emotion recognition experiments, demonstrate that PCMSFE achieves higher recognition accuracy than MSFE. (b) For EEG feature classification, we construct an IGWO-optimized SVM parameter model improved through cosine nonlinear convergence factor and dynamic-static position update strategies. Using nine benchmark test functions and comparing emotion recognition accuracy under PCMSFE features, IGWO-SVM outperforms GWO, PSO, FA (firefly algorithm), and GA in optimizing SVM. Additionally, we compare valence and arousal classification under high and low liking conditions, revealing that recognition rates are higher when liking is low.

1.1 DEAP Dataset

DEAP (database for emotion analysis using physiological signals) [19] is a publicly available database proposed by Koelstra et al., providing a multi-channel dataset for human emotional state analysis. The database integrates EEG signals, physiological signals, and video signals, offering open datasets for experimental research. It records EEG and peripheral physiological signals from 32 subjects.

Thirty-two healthy participants were involved in the experiment. Before the experiment, subjects were informed about the experimental protocol and the meaning of self-assessment scales. During the experiment, subjects watched 40 music videos designed to elicit significant emotional changes. The experiment was conducted in two laboratory environments with controlled lighting. EEG and peripheral physiological signals were recorded using a Biosemi ActiveTwo system on a dedicated recording PC (Pentium 4, 3.2 GHz). Music videos were presented on a 17-inch screen. To minimize eye movements, all video stimuli approximately filled 2/3 of the screen, with subjects seated approximately 1 meter from the screen. Before the experiment, each subject was asked about their comfort level and adjustments were made when necessary. After 20 trials, subjects rested while experimenters checked signal quality and electrode positions.

The experimental procedure consisted of: (a) displaying the current video number on screen for 2 seconds to inform subjects of experimental progress; (b) 5 seconds of baseline recording; (c) 1-minute music video presentation; (d) subjects performing self-assessment of arousal, valence, liking, and dominance. The dataset has undergone simple preprocessing, including downsampling to 128 Hz, filtering between 4.0–45 Hz, and using blind source separation to remove ocular artifacts. Each data record totals 63 seconds, comprising 60 seconds of experimental data and 3 seconds of baseline data. This study uses the 60-second data segments for experiments.

1.2 EEG Signal Processing Procedure

The general EEG emotion recognition process includes data preprocessing, feature extraction, and feature classification. This paper additionally incorporates data segmentation and stacking to increase feature quantity and avoid poor classification due to insufficient data volume. The main processing steps and framework are illustrated in Figure 1 [Figure 1: see original paper].

(a) **Data Preprocessing.** EEG signal noise may originate from static or electromagnetic fields generated by surrounding equipment. In addition to external noise, EEG signals are severely affected by human factors such as body movements and blinking [20]. The DEAP database has undergone corresponding preprocessing. Based on prior experience, Alpha and Beta waves significantly impact results while other bands have minimal influence [21]; therefore, only these two bands are extracted for experiments. Signals are filtered using bandpass FIR filters to remove noise below 8 Hz and above 30 Hz.

(b) **Data Segmentation.** Alpha and Beta band data are segmented using a 20-second moving window on the 60-second data segments with 10-second overlap, yielding five data segments of 20 seconds each.

(c) **Feature Extraction.** Eight channels with significant influence (four pairs: FP1-FP2, AF3-AF4, F3-F4, F7-F8) are selected for feature extraction. Power spectral features from these eight channels in each segment are extracted, and both MSFE and PCMSFE features are calculated for subsequent comparison of their impact on recognition rates.

(d) **Data Stacking.** The 12 features extracted from each data segment are serially stacked in parallel, resulting in 12 Alpha band features + 12 Beta band features = 24 features per group. Each subject has 40 (trials) $\times$ 5 = 200 samples, with 80% randomly selected for training and the remaining

20% for testing.

(e) **Feature Classification.** The IGWO-optimized SVM parameter model (denoted as IGWO-SVM) is applied for EEG emotion recognition, classifying valence, arousal, dominance, and liking from the database. IGWO-SVM is compared with SVM models optimized by GWO, PSO, FA, and GA. Additionally, emotion recognition rates under MSFE and PCMSFE features using IGWO-SVM are compared. Furthermore, IGWO-SVM is used to compare classification effects of valence and arousal under different liking levels.

1.3 Piecewise Complex Multi-Scale Fuzzy Entropy

EEG signals are non-stationary random signals, making traditional waveform and energy analysis insufficient. Nonlinear dynamic features are therefore applied to EEG research. Entropy is a crucial parameter for measuring brain complexity. Approximate entropy and sample entropy measure time complexity with strong anti-noise capabilities and short data requirements. However, approximate entropy lacks consistency in parameter selection, while sample entropy requires template matching for meaningful calculation. Fuzzy entropy, as an improvement over sample entropy, provides smoother transitions during parameter changes and stronger anti-interference capabilities. Nevertheless, fuzzy entropy measures time sequence complexity at a single scale. Literature [10] introduced multi-scale fuzzy entropy (MSFE) to measure complexity across different scale factors, but this algorithm is prone to data loss and inaccurate entropy calculations. Therefore, this paper employs a piecewise composite multi-scale fuzzy entropy algorithm for EEG signal feature extraction.

1.3.1 Traditional Multi-Scale Fuzzy Entropy

The MSFE method first coarse-grains the original sequence to establish new coarse-grained vectors. For a given embedding dimension m and similarity tolerance r, the similarity between vectors is defined using a fuzzy function. The multi-scale fuzzy entropy is defined as:

When N is finite, the expression becomes:

However, MSFE defined by these equations suffers from data loss, inaccurate results, or undefined entropy values.

1.3.2 Multi-Scale Fuzzy Entropy Based on Piecewise Composite Strategy

To address MSFE limitations, this paper adopts piecewise coarse-graining and composite multi-scale fuzzy entropy calculation. Piecewise coarse-graining resolves data loss when data length is not an integer multiple of the scale factor. Composite multi-scale entropy calculation addresses inaccurate computation for short time series at large scale factors and reduces the probability of undefined entropy. The main processing steps are:

(a) **Piecewise Coarse-Graining of Original Sequence.** Traditional coarse-graining compresses the original time sequence by scale factor , causing data loss when the data length is not an integer multiple of . Inspired by improvements to multi-scale sample entropy coarse-graining [22], we apply piecewise coarse-graining to multi-scale fuzzy entropy. The coarse-grained sequence is defined as:

where is the scale factor and N is the time series length.

(b) **Composite Multi-Scale Fuzzy Entropy Calculation.** MSFE may yield inaccurate results when the scale factor is too large, resulting in excessively short data lengths. While methods from literature [23] provide some improvement, issues of inaccuracy and undefined entropy remain. This paper employs a complex multi-scale fuzzy entropy method (CMSFE) to enhance computational precision:

This composite approach reduces the probability of inaccurate or undefined entropy by averaging traditional MSFE values across scales.

1.4 Grey Wolf Algorithm

SVM is widely used for EEG feature classification, though its performance is heavily influenced by internal parameters. Compared to PSO and GA, GWO requires fewer parameters and has a simpler principle, but it is prone to local optima and inflexible position updates. This paper improves GWO using a cosine nonlinear convergence factor to balance global and local search, and a hybrid harmonic-static mean position update strategy.

1.4.1 Basic Grey Wolf Algorithm

GWO simulates grey wolf pack hunting behavior. The population has a strict hierarchy: the highest-ranking alpha ( ) wolf leads hunting, food distribution, and decision-making. The beta ( ) wolf assists and substitutes when is absent. The delta ( ) wolf follows and , balancing internal relationships and encircling prey during hunting. The omega ( ) wolves execute hunting strategies.

During hunting, coefficient variables A and C are calculated based on convergence factor a. When $|A| > 1$, the pack expands its search range for better prey (global search); when $|A| < 1$, the pack contracts the encirclement (local search). The convergence factor a is calculated as:

where t is the current iteration and t_max is the maximum iteration count, with a linearly decreasing from 2 to 0. After detecting prey location, distances D_ , D_ , D_ from , , wolves to prey are calculated to determine prey position. The step lengths and directions of wolves toward , , wolves are defined, and the final forward direction of wolves is determined.

When a decreases to 0, the grey wolf population attacks and captures prey, yielding the optimal solution.

1.4.2 Improved Grey Wolf Algorithm

1) Cosine Nonlinear Convergence Factor

Swarm intelligence algorithms face a trade-off between global and local search, easily falling into local optima. The linear decrease of a from 2 to 0 does not fully reflect the actual nonlinear search process. Therefore, this paper adopts a cosine nonlinear convergence factor:

2) Position Update Combining Harmonic and Static Means

In the basic GWO, position updates use static averaging of the top three individuals, which can lead to inflexible updates and difficulty finding optimal solutions. This paper employs a hybrid approach combining harmonic mean and static mean. When , , wolves detect prey location, wolves approach prey under their guidance. The step lengths and directions are calculated, and position updates are completed by combining harmonic mean (Equation 26) and static mean (Equation 17).

A threshold is set: when the fitness difference between and wolves exceeds the threshold, harmonic mean updates positions; when below the threshold, static mean is used. Through repeated experiments, the threshold is set to 0.1 in this paper.

1.4.3 IGWO Algorithm Implementation Steps

(a) Set upper and lower bounds for wolf pack variables, randomly initialize wolf positions within bounds. Initialize GWO parameters including population size N, maximum iterations, and target function values as infinity.

(b) Calculate each wolf' s fitness value to determine prey location. Select the top three wolves as , , , and update their objective function values and positions with C and g values.

(c) During prey search, update positions using Equation (20). During capture, update , , positions using Equations (23)-(25). Calculate step lengths and directions of wolves toward , , using Equations (17) and (26) to update the entire pack.

(d) Save the optimal individual position and value during iterations. If maximum iterations are reached, output the optimal position and value; otherwise, return to step (b).

1.5 Improved Grey Wolf Algorithm for SVM Model Optimization

(a) Initialize the grey wolf population, where each individual’ s position consists of SVM parameters C (penalty coefficient, tolerance for errors) and g (RBF kernel function parameter). Initialize population size, maximum iterations, C and g ranges, , , positions, and objective function values.

(b) Apply initialized C and g to SVM training and testing, using the test error rate as the fitness value to be minimized.

(c) Update , , objective function values based on fitness. If fitness is better than ’ s function value, update ; if between and , update ; if between and , update . Save corresponding C and g values.

(d) Update convergence factor a using Equation (18), randomly obtain r_1 and r_2, calculate , , positions, and compute step lengths and directions for position updates. Return to the optimal individual position.

(e) When maximum iterations are reached, output ’ s current position and optimal values (C, g) and training accuracy.

2 Experimental Results and Analysis

The simulation environment uses an Intel® Core™ i5-8400M CPU @2.80 GHz, 8 GB RAM, Windows 10, MATLAB R2016b.

2.1 Performance Analysis of PCMSFE Algorithm

To test PCMSFE feature performance, random white noise and 1/f noise with 512, 1024, and 2048 sampling points were extracted for comparison between MSFE and PCMSFE. Parameters were set as: scale factor = 1~15, embedding dimension m = 2, similarity tolerance r = 0.2*std (std = standard deviation), boundary gradient n = 2. Figures 2 Figure 2: see original paper-(c) show PCMSFE vs. MSFE results for random white noise at 512, 1024, and 2048 points. Figures 3 Figure 3: see original paper-(c) show results for 1/f noise. Random white noise complexity gradually decreases with increasing scale, while 1/f noise complexity stabilizes. At 512 points, MSFE standard deviation exceeds PCMSFE in both noise types, with smaller mean errors across scales. As sampling points increase to 1024 and 2048, MSFE standard deviation decreases but remains larger than PCMSFE. For 1/f noise at 2048 points, PCMSFE curves are smoother with similar standard deviation. This demonstrates PCMSFE’ s superiority over MSFE for short data lengths.

2.2 Performance Analysis of IGWO Algorithm

To test IGWO performance, nine benchmark functions [24] (F1-F9) were selected: Sphere Model, Generalized Rosenbrock’ s Function, Quartic Function, Generalized Rastrigin’ s Function, Generalized Griewank Function, Ackley’ s

Function, Six-Hump Camel-Back Function, Branin Function, and Goldstein-Price Function. F1-F3 are unimodal, F4-F6 are multimodal, and F7-F9 are fixed-dimension multimodal functions. All algorithms used population size 30 and maximum iterations 500 for fairness.

Table 1 shows results from 30 independent runs. For unimodal functions, IGWO1 achieves better mean and standard deviation than GWO on F1, and lower standard deviation on F3. IGWO shows mean closer to 0 on F1 with lower standard deviation across all three functions. For multimodal functions, IGWO reaches optimal solution 0 on F4 and F5 for both mean and standard deviation. IGWO1, IGWO2, and IGWO achieve lower means than GWO on F6 with zero standard deviation. For fixed-dimension functions, all algorithms reach optimal solutions on F7 and F9, with IGWO1 achieving zero standard deviation on F7 and IGWO2/IGWO showing lower standard deviation than GWO on F9.

IGWO demonstrates advantages across most functions, improving search precision and stability. Figure 4 [Figure 4: see original paper] shows convergence curves for F1 and F4, confirming IGWO' s significantly faster convergence speed and higher precision compared to GWO, validating the proposed improvements.

2.3 EEG Emotion Recognition Experiments

Experimental samples were derived from the DEAP database. Bandpass FIR filters removed noise below 8 Hz and above 30 Hz. Experiments were divided into four categories: valence, arousal, dominance, and liking. Additionally, valence and arousal recognition rates under high/low liking conditions were compared. Since DEAP is not specifically designed for liking evaluation and some subjects exhibit imbalanced liking labels, subjects with high/low liking ratios below 0.3 were excluded, leaving 21 subjects for analysis. The database was divided into high-liking and low-liking datasets for valence and arousal classification experiments, with 80% randomly selected for training and 20% for testing. To ensure fairness, each subject' s data quantity was standardized to the smaller label count.

To validate IGWO-SVM performance for EEG emotion recognition, it was compared with SVM models optimized by GWO, PSO, GA, and FA. All optimization algorithms used population size 20 and maximum iterations 200 to ensure convergence. SVM parameters were set as C [0.01, 100], g [0.01, 100]. IGWO-SVM (marked as OURS), GWO-SVM, PSO-SVM, GA-SVM, FA-SVM, and standard SVM models were established. Additionally, a traditional MSFE feature with IGWO-SVM classification model (MSFE-IGWO) was created.

Figure 5 [Figure 5: see original paper] compares average recognition rates across models. GWO-SVM outperforms other models, confirming grey wolf algorithm' s superior SVM optimization. IGWO-SVM achieves higher classification performance than all other models on valence, arousal, dominance, and liking, validating the GWO improvements. MSFE-IGWO shows lower recognition rates than IGWO-SVM across all dimensions, demonstrating PCMSFE' s superior discriminative power over MSFE.

Table 2 shows recognition time per subject. IGWO-SVM requires the shortest time, indicating improved efficiency. Table 3 presents average recognition rates, standard deviations, maximum and minimum values for each model across four dimensions. IGWO-SVM achieves the highest average recognition rates with lower standard deviations than most models, reaching maximum recognition rates of 100%.

Figure 6 [Figure 6: see original paper] illustrates the impact of liking levels on valence and arousal. Low-liking conditions yield better classification performance than high-liking conditions and higher recognition rates than the full dataset, suggesting that liking level significantly affects valence and arousal classification, with lower liking producing superior emotion recognition.

3 Conclusion

This paper constructs a piecewise composite multi-scale fuzzy entropy method for EEG signal features, using piecewise coarse-graining to solve data loss problems and composite multi-scale fuzzy entropy to prevent computational inaccuracy from large scale factors. An improved grey wolf algorithm optimizes SVM parameters for EEG emotion recognition, employing cosine nonlinear convergence factor and dynamic-static position update strategies. The model achieves classification across valence, arousal, dominance, and liking dimensions, and compares valence/arousal classification under different liking levels. Compared to other spontaneous or evoked EEG signals, the proposed algorithm reflects subjects' emotional states more accurately, providing a foundation for EEG applications in human-computer interaction and auxiliary lie detection.

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