[redacted] signal processing and [redacted] using [redacted]

[redacted], [redacted], [redacted], [redacted], [redacted], [redacted], [redacted]
[redacted]
[redacted], China
*Corresponding author's e-mail: [redacted]

***Abstract*—As an important task in the advanced stage of artificial intelligence, the research of emotional [redacted] has received more and more attention in recent years. In order to improve the accuracy of [redacted] signal [redacted], in this paper, Fast Fourier Transform ([redacted]) and [redacted] (CWT) are used to extract the features of [redacted] signals on the DEAP data set and build two [redacted] models for [redacted]. The results show that the proposed algorithm is effective for [redacted] signal [redacted]. The average recognition accuracy of emotion [redacted] can reach 75.9%; the arousal can reach 79.3%; the like/dislike can reach 80.7%. This research can provide practical application reference for continuous dimension emotion automatic analysis and machine recognition.**

***Keywords-component;* [redacted]; [redacted]; *CWT;* [redacted]; [redacted]**

[redacted] [redacted]

[redacted] is a multidisciplinary research field integrating cognitive science, psychology, computer science, and neuroscience. It is a difficult and hot spot in the field of cognitive science. With the enhancement of computer computing power, the cost of implementing machine learning algorithms is greatly reduced, and building a machine learning algorithm model can effectively improve the accuracy and robustness of [redacted]. At the same time, with the development of non-invasive sensing technology and human-computer interaction technology, [redacted] signals are gradually introduced into the field of [redacted] research due to their strong objectivity and high accuracy of classification and recognition.

[redacted] of [redacted] signals has achieved good classification results under traditional machine learning classifiers. Reference [1] used [redacted] least squares support vector machines (LS-[redacted]) and back propagation artificial neural network ([redacted]), which are effective the two-category [redacted] is performed on the [redacted]-arousal model and the accuracy rate reaches 61.17% and 64.84%. Reference [2] extracted [redacted] signal features from the DEAP data set by combining maximum correlation, minimum redundancy and principal component analysis, and fused high-dimensional features, using support vector machines ([redacted]) for classification, and accurate classification in terms of [redacted] and arousal the accuracy were 72.45% and 76.1%. Reference [3] used an efficient feature selection method and a kernel-based classifier to classify emotions on the standard [redacted] data set, and the accuracy of the [redacted] and arousal on the [redacted] classifier reached 73.06%, 73.14%.

The increase in computer processing speed and computing power provides the possibility for the design and implementation of deep learning networks. Reference [4] extracted the median, mean, variance, and kurtosis of the [redacted] signal on the DEAP data set, and used a [redacted] ([redacted]) as the classifier to achieve [redacted]-[redacted]. [redacted] was performed on the degree of emotion model, and the average classification accuracy rates of 81.40% and 73.36%. Reference [5] divided the [redacted] signal into multiple time periods on the DEAP data set and extracted its features and used the Long-Short term memory ([redacted]) algorithm for dimensional emotion classification, and the accuracy rates were 73.9% and 73.5% respectively; Reference [6] introduced the deep belief networks with glia chains ([redacted]-[redacted]) model to extract high-level abstract features in the time domain, frequency domain, and time-frequency domain of the [redacted] signal and used restricted [redacted] machines ([redacted]) to achieve emotion classification accuracy rates of 81.40% and 73.36%.

At present, in [redacted] signal [redacted], the accuracy of continuous [redacted] based on the dimensional emotion model is generally not high, especially for the four-category [redacted] research, which cannot meet the application needs, and the individual emotional physiological characteristics vary greatly. The characteristics of [redacted] related to emotions are not sufficient and the differences are not significant. Therefore, in response to these problems, this article uses two types of feature extraction tools on the dimensional emotional data set: fast Fourier transform ([redacted]) and [redacted] (CWT), and constructs two [redacted] models for classifying [redacted] signals. By comparing the experimental results of the two proposed models with other emotion classification task models, the [redacted] model obtained a better recognition accuracy, which laid a solid foundation for the automatic [redacted] and recognition of [redacted].

II. MATERAILS AND METHODS

The steps of [redacted] based on [redacted] signals generally include: emotion induction, [redacted] signal collection, signal preprocessing, [redacted] feature extraction and emotion learning classification.

In this paper, the data set is DEAP [7]. The overall design framework is shown in [redacted]. 1. First, a bandpass filter is used to

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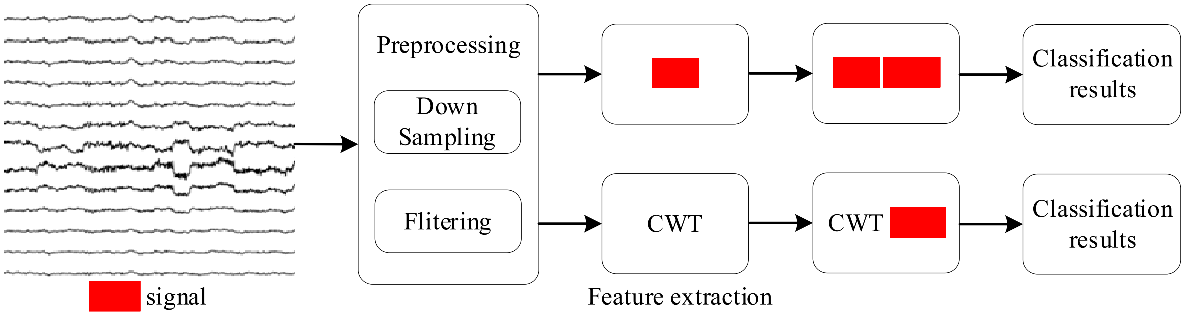
preprocess the original [redacted] signal to filter out high-frequency clutter. Second, a fast Fourier transform ([redacted]) and [redacted] (CWT) perform feature extraction on [redacted] signals. Finally, through neural network learning and training, the classification results are output.

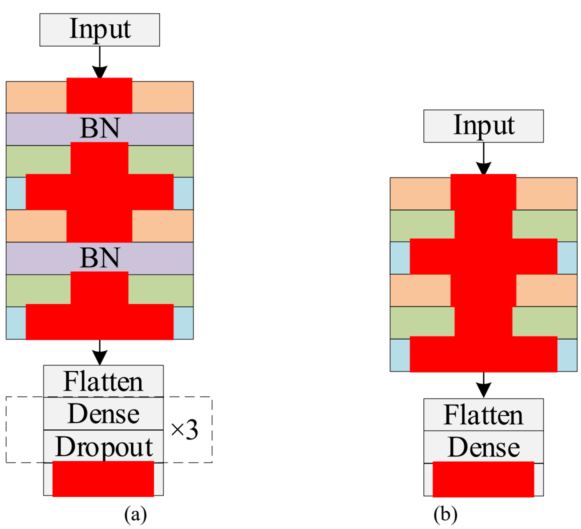


[redacted]ure 1. Overall design framework

A. [redacted] Model with [redacted]

[redacted], the raw [redacted] signal is preprocessed, and feature extraction is performed through the [redacted] algorithm. Split the processed data and labels into a training-test set at a ratio of 80-20, apply one-hot encoding to the labels, and use a standard scalar to normalize the data in order to obtain better accuracy.

Maximum pooling is implemented for the convolution part, and the rectified linear unit (Relu) activation function is used for the dense layer. Several batch normalization and dropout layers were inserted to prevent overfitting. For the final classification layer, use the [redacted] activation function to output the probability estimate for each class. The convolution part is shown in [redacted]. 2(a).



[redacted]ure 2. [redacted] (a); CWT model (b)

B. [redacted] Model with CWT Feature Extraction

The CWT model utilizes the CWT algorithm from PyWavelets. This method uses the mother wavelet and the scale list of the inspection signal as the input signal. The mother wavelet is a "Morlet" wavelet.

Similar to the [redacted], the CWT model is implemented through One-Hot and other methods of encoding, standard scalar normalization, and [redacted] cross-validation. The model architecture is redesigned as shown in [redacted]. 2(b). In order to better adapt to the DEAP data set and produce better results. The CWT model reduces the number of dropout layers and the number of batch normalization layers to prevent large peaks and fluctuations in the verification loss.

III. EXPRIMENTAL RESULTS AND DISCUSSION

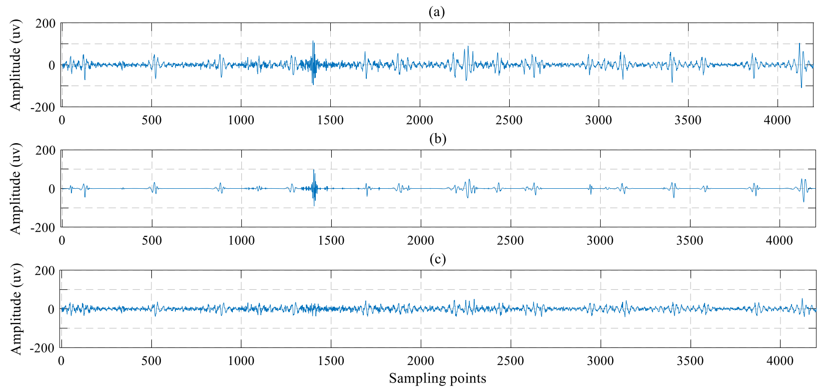
This experiment was trained and tested on the windows10 system and the [redacted] Quadro P5000 platform. Considering computing resources and computing time, this experiment uses the original [redacted] data of 3 subjects (subjects 01, 02 and 03).

A. DEAP data set and preprocessing

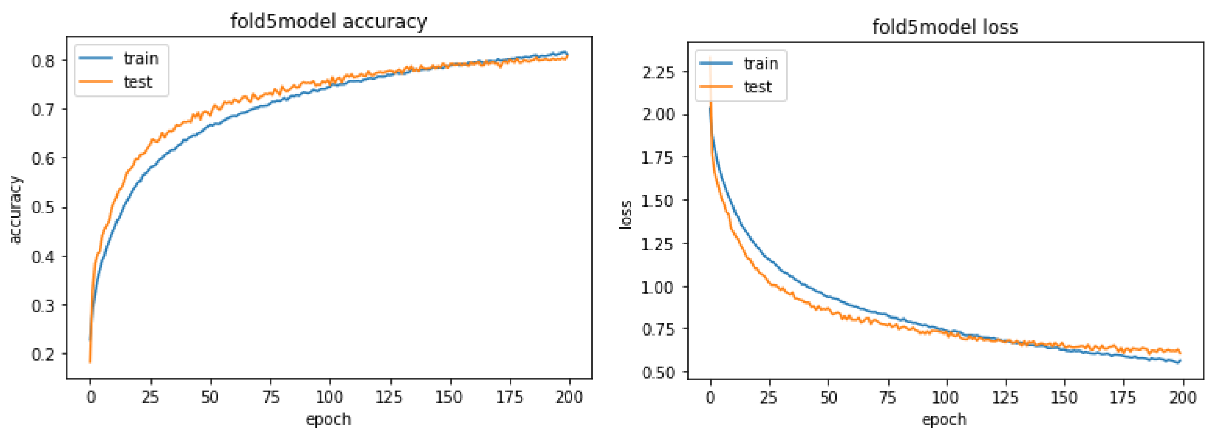
The DEAP data set contains 32 channels of [redacted] signals of 32 subjects and 8 channels of peripheral [redacted]. This article only uses 32-channel [redacted] signals as experimental data: [redacted] signals are first sampled at 512Hz, then the sampling rate is reduced to 128Hz, and the bandpass frequency filtering of 40-45.0Hz is used to remove [redacted] artifacts, as shown in [redacted]. 3. Each participant watched 40 emotional music videos, each with a duration of 1 minute. After the subjects watched each video, they scored the degree of arousal, [redacted] preference and dominance, with a score of 1-9. The evaluation value from small to large indicates that the various indicators are from negative to positive, from strong to weak.

[redacted] of [redacted] Model

The [redacted] model with [redacted] feature extraction was trained with [redacted] cross-validation ([redacted]) over 200 epochs, and the model was confirmed to converge. [redacted]. 4 shows a pair of training and testing accuracy and loss curves of the model during 5 folds. From the results, it can be seen that the [redacted] produces good results, and the accuracy value is significantly higher than the chance level. This shows that the fast Fourier transform model is also very versatile for invisible data, because the training and testing results are comparable. Among the 4 classes, the performance of the [redacted] is quite stable, with like/dislike classes, resulting in the best test accuracy result of 81.2%.

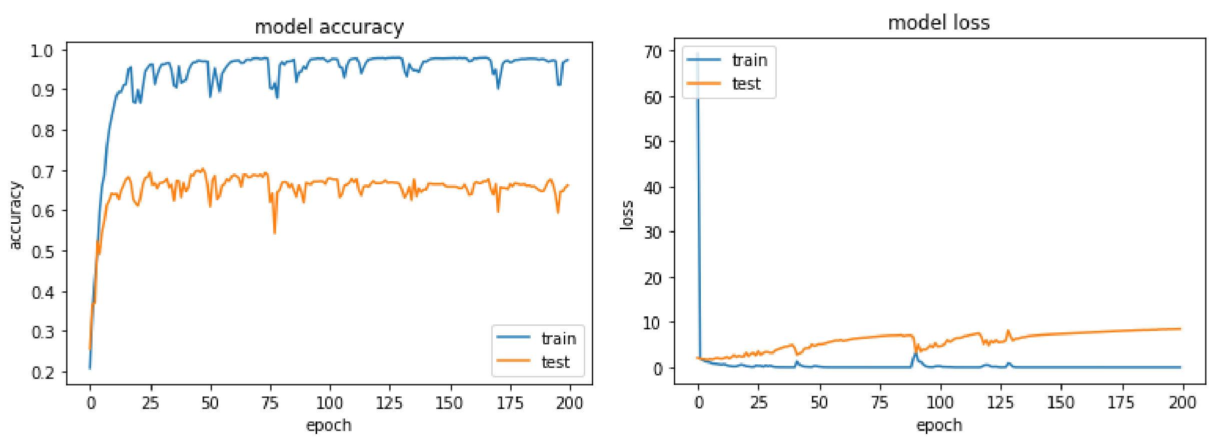


[redacted]ure 3. raw [redacted] signal (a); Filtered noise signal (b); [redacted] signal (c)



(a) (b)

[redacted]ure 4. [redacted] model accuracy (a); [redacted] model loss (b)



(a) (b)

[redacted]ure 5. CWT [redacted] model accuracy (a); CWT [redacted] model loss (b)

[redacted] *of the CWT* [redacted] *Model*

Similar to [redacted] model, [redacted] model with CWT feature extraction has been trained on 200 epochs. [redacted]. 5 shows a pair of training and testing accuracy and loss curves of the model. It can be seen that CWT model produces good results, with training and testing accuracy higher than the opportunity level, and impressive training accuracy and loss. The Like/Dislike class shows the best results, with the test accuracy of 66.5% and the training accuracy of 95.6%.

However, it is worth noting that the model shows a high level of verification loss, which indicates that CWT model over-fits the training data. The loss graph confirms this finding. With the increase of epoch, the verification loss is different from the training loss.

[redacted] [redacted] between [redacted] and [redacted]

The results of [redacted] and [redacted] are shown in table 1. It can be seen that [redacted] [redacted] outperforms CWT model in every emotion category of the DEAP data set, with an average test accuracy of 78%, while CWT model has an average test accuracy of 65%. Among the three different emotions, it is worth noting that [redacted] and [redacted] have the best results on Like/Dislike class, followed by Arousal and [redacted] class. This may indicate that compared with other types of emotions (such as arousal), there is a higher correlation between likes and dislikes and individual [redacted] signal frequency.

[redacted]. Results from the [redacted] and [redacted]

Classes	Test accuracy	
	[redacted]	CWT Model
Arousal	79.4%	63.9%
[redacted]	76.0%	63.0%
Like/dislike	81.2%	67.5%

E. Compared with other classification methods

The comparison between [redacted] and [redacted] and other recognition models were completed and shown in table 2, all the datasets utilized the DEAP datasets. Reference [5] used [redacted] recurrent neural network, and accurate classification in terms of [redacted] and arousal the accuracy were 73.9% and 73.5%. Reference [6] used [redacted] network model, and the accuracy of the [redacted] and arousal reached 78.2%, 77.1%. Reference [8] used dual-tree complex wavelet packet transform for three-dimensional [redacted] [redacted] and classification, the classification accuracy rates of arousal, [redacted], and like/dislike are 66.2%, 64.3%, and 70.2%, respectively. This paper proposes two three-dimensional emotion classification models. The classification accuracy of CWT [redacted] Model in [redacted], arousal, and like/dislike were 63.9%, 63.0%, and 67.5% respectively; and the [redacted] [redacted] Model is in [redacted], arousal, and like/dislike were 79.4%, 76.1%, and 81.2%. It can be seen from the summary of the results that although the performance of CWT [redacted] Model is inferior to other recognition models, it is still considerable compared with [redacted] model in [8]. On the other hand, the [redacted] [redacted] Model is not inferior to other classification recognition models. It has achieved very impressive experimental results in both the two-class and three-class experiments, especially in the category of like/dislike, reaching 81.2%. This shows that the [redacted] [redacted] Model is indeed well generalized to [redacted] data.

[redacted]. Accuracy comparison with other models

Classes/models	Arousal	[redacted]	Like/dislike
Reference [5]	73.9%	73.5%	-
Reference [6]	78.2%	77.1%	-
Reference [8]	66.2%	64.3%	70.2%
CWT [redacted] Model	**63.9%**	**63.0%**	**67.5%**
[redacted] [redacted] Model	**79.4%**	**76.1%**	**81.2%**

IV. CONCLUSION

In this paper, basing on the DEAP data set, fast Fourier transform and [redacted] are used to extract the features of [redacted] original signals, and input the extracted shallow features into the [redacted] [redacted] [redacted] for learning and training. Emotions are classified and identified in three dimensions: arousal, [redacted] and likes/dislike. By comparing two different feature extraction algorithms, it is proved that the fast Fourier transform [redacted] model achieves better classification and recognition effect. Comparing with other methods, [redacted] feature extraction algorithm has achieved higher recognition accuracy and is more suitable for emotion classification tasks. This research can be applied to [redacted] in medical treatment, education, human-computer interaction and criminal investigation.

ACKNOWLEDGMENT

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