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Recognition Method of Limb Motor Imagery EEG Signals Based on Integrated Back-propagation Neural Network

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Abstract: In this paper, in order to solve the existing problems of the low recognition rate and poor real-time performance in limb motor imagery, the integrated back-propagation neural network (IBPNN) was applied to the pattern recognition research of motor imagery EEG signals (imagining left-hand movement, imagining right-hand movement and imagining no movement). According to the motor imagery EEG data categories to be recognized, the IBPNN was designed to consist of 3 single three-layer back-propagation neural networks (BPNN), and every single neural network was dedicated to recognizing one kind of motor imagery. It simplified the complicated classification problems into three mutually independent two-class classifications by the IBPNN. The parallel computing characteristic of IBPNN not only improved the generation ability for network, but also shortened the operation time. The experimental results showed that, while comparing the single BPNN and Elman neural network, IBPNN was more competent in recognizing limb motor imagery EEG signals. Also among these three networks, IBPNN had the least number of iterations, the shortest operation time and the best consistency of actual output and expected output, and had lifted the success recognition rate above 97 percent while other single network is around 93 percent.

Keywords: IBPNN, motor imagery, EEG, recognition, BPNN, Elman neural network.

INTRODUCTION

Electroencephalogram (EEG) signals indicate the spontaneous and rhythmic electrical activity of brain cells contain enormous biological information and may reflect the physiological and psychological states of humans [1]. When people just imagine body movements but do not execute, the brain produces the same EEG pattern as the action performed. Thus we can use mind to control the external environment so as to achieve the action we thought by correctly and timely recognizing motor imagery EEG signals. But as the EEG signals belong to non-stationary ones, having characteristics of randomness, nonlinearity, being susceptible to disturbance for weak signals, etc. [2], there are many difficulties in the analysis of motor imagery EEG signals, especially for multi-class problems, and many classification methods are based on two kinds of motor imagery EEG signals for recognition. Nowadays, the recognition algorithm for motor imagery EEG signals is more focused on briefness, accuracy and celerity, which may make the human-computer interaction system to obtain the ideal recognition result within the shortest training time.

Currently, there are different methods for classifying the EEG signals. These methods, generally, could be categorized into two basic categories, one of which is called linear classification method and the other is called the nonlinear classification one [3]. The linear classification method contains Fisher linear classification method and the approximate entropy (ApEn) classification method; while the nonlinear classification method mainly includes the artificial neural network (ANN) and support vector machine (SVM) methods. Among the above methods, the ANN method is widely applied in various fields for its simple operation, strong adaptiveness and excellent prediction capability. These commonly used neural networks, however, may not ensure to well predict the new samples, that is to say that such networks are of poor generalization ability [4]. Moreover, factors of the sample size, parameter setting, distribution of training sets and testing sets, etc., may affect the calculation accuracy and operation time of ANN [5]. In order to avoid the influences of the above problems, and to improve the data recognition rate, this paper has proposed to research the limb motor imagery EEG signals by utilizing IBPNN.

Since Hansen and Salamon [6] first put forward the neural network ensemble (NNE) method in 1990, the neural network, after years of development, has been widely used in aspects of pattern recognition, risk prediction, etc. In 2008, Zhang Lei, *et al*. [7] used the integrated neural network in authenticating off-line signature and obtained the higher recognition rate. In 2012, Su C and Xiao NF [8] used the integrated BP network and received the higher recognition rate in face identification. In 2013, Lee H, *et al.* [9] also used the integrated neural network to recognize domain actions and got great recognition rate. Moreover, Qin LL, *et al.* [10]

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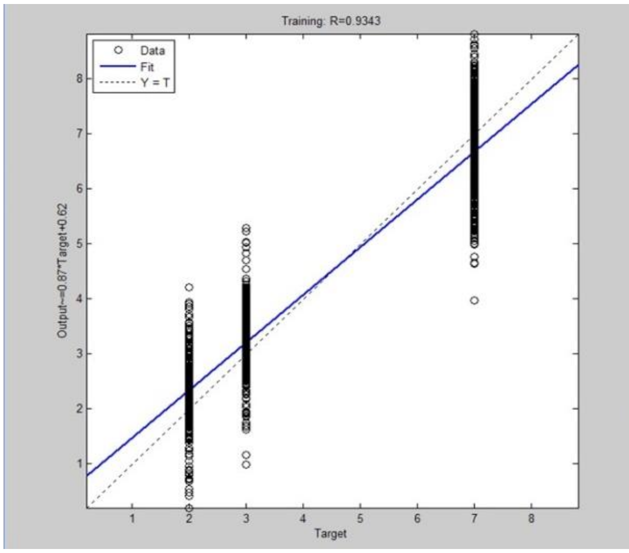

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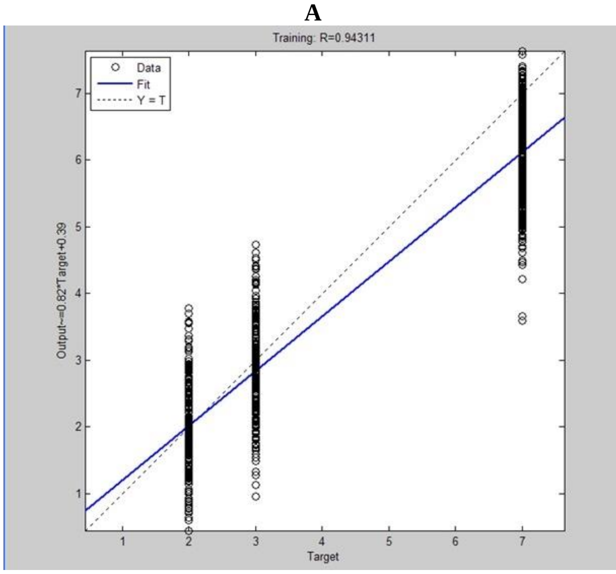

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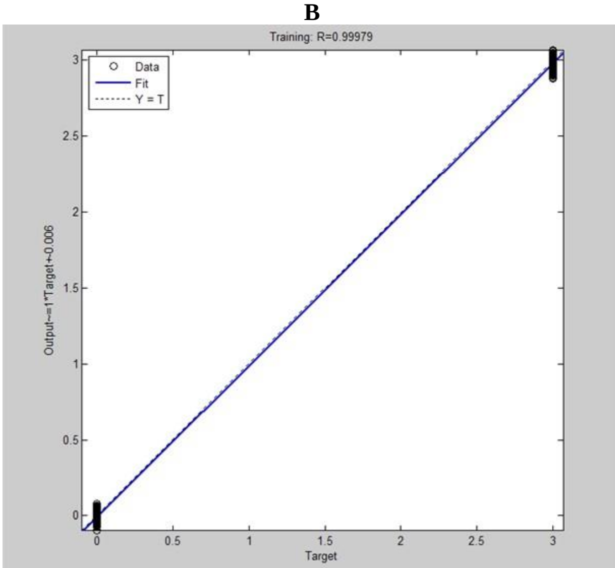

C

Fig. (10). Linear Regression Graph for Each Network. (**A**: BPNN; **B**: Elman Neural Network; **C**: IBPNN).

4. DISCUSSIONS

In this paper, we have mainly conducted the pattern recognition for EEG signals based on three different motor imageries by utilizing the method of IBPNN, and we have also contrasted IBPNN with BPNN in four aspects of iterations, operation time, the consistency of actual output and expected output, and the success recognition rate. The experimental results has shown that, when the data categories reach three, the correct recognition rate of IBPNN is significantly higher than that of a single neural network, and the operation speed is faster as well. The IBPNN overcomes the problems of low generalization, intricate scale as well as long operation time for BPNN. Therefore, IBPNN is more competent in recognizing EEG signals of motor imageries.

The IBPNN is composed of several sub-networks, which are independent from each other. Thus each sub-network has its own proper job and may not be influenced by other ones. In the training stage for networks, each sub-network has to achieve one relationship from input to output, and then the structure and training process of sub-networks will be simplified. With these characteristics, IBPNN cannot only enhance the advantages of sub-networks, but also may reduce the weakness of it.

Due to the specificity of these EEG signals, we cannot guarantee the accuracy of every set of data. Therefore, the rate for IBPNN recognizing EEG signals is not perfect. Moreover, IBPNN itself has certain limitations as well; there is lack of theoretical basis for the choice of neurons in hidden layer, what's more, the initial weights and thresholds for networks are acquired randomly. The recognition rate of motor imagery EEG signals may also be influenced by the above-mentioned limitations. In our future work, therefore, we will design a BCI system based on IBPNN while improving the IBPNN algorithm, so as to get a friendlier environment for human-computer interaction.

Fig. (11). Average Recognition Rate of Each Network.

ABBREVIATIONS

ANN	=	Artificial neural network
ApEn	=	Approximate entropy
BPNN	=	Back-propagation neural networks
BCI	=	Brain-computer interface
EEG	=	Electroencephalogram
IBPNN	=	Integrated back-propagation neural network
LVQ	=	Learning Vector Quantization
MSE	=	Mean square error
NNE	=	Neural network ensemble
WNN	=	Wavelet neutral network
SNR	=	Signal-to-noise ratio
SVM	=	Support vector machine

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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