APPLICATION OF BACK PROPAGATION NEURAL NETWORK IN SPORTS FATIGUE INDICATORS

APLICAÇÃO DA REDE NEURAL DE RETROPROPAGAÇÃO EM INDICADORES DE FADIGA ESPORTIVA

APLICACIÓN DE LA RED NEURONAL DE RETROPROPAGACIÓN EN INDICADORES DE FATIGA DEPORTIVA

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ABSTRACT

Introduction: High-intensity rehabilitation training will produce exercise fatigue. Objective: A backpropagation (BP) network neural algorithm is proposed to predict sports fatigue based on electromyography (EMG) signal images. Methods: The principal component analysis algorithm is used to reduce the dimension of EMG signal features. The knee joint angle is estimated by the regularized over-limit learning machine algorithm and the BP neural network algorithm. Results: The RMSE value of the regularized over-limit learning machine algorithm is lower than that of the BP neural network algorithm. At the same time, the ρ value of the regularized over-limit learning machine algorithm is closer to 1, indicating its higher accuracy. Conclusions: The model training time of the regularized over-limit learning machine algorithm has been greatly reduced, which improves efficiency. ***Level of evidence II; Therapeutic studies - investigation of treatment results.***

Keywords: Exercise,high-intensity; Fatigue; Knee Joint.

RESUMO

Introdução: O treinamento de reabilitação de alta intensidade produzirá fadiga ao exercício. Objetivo: Um algoritmo neural de backpropagation network (BP) é proposto para prever a fadiga esportiva com base em imagens de sinais de eletromiografia (EMG). Métodos: O algoritmo de análise de componente principal é usado para reduzir a dimensão das características do sinal EMG. O ângulo da articulação do joelho é estimado usando o algoritmo de aprendizado de máquina de limite regularizado acima e o algoritmo de rede neural BP. Resultados: o valor RMSE do algoritmo de aprendizado de máquina acima do limite regularizado é menor que o do algoritmo de rede neural BP. Ao mesmo tempo, o valor de ρ do algoritmo de aprendizado de máquina acima do limite regularizado está próximo de 1, indicando sua maior precisão. Conclusões: O tempo de treinamento do modelo de algoritmo de aprendizado de máquina acima do limite regularizado foi bastante reduzido, o que melhora a eficiência. ***Nível de evidência II; Estudos terapêuticos: investigação dos resultados do tratamento.***

Descritores: *Exercício, alta intensidade; Fadiga; Articulação do Joelho.*

RESUMEN

Introducción: El entrenamiento de rehabilitación de alta intensidad producirá fatiga por ejercicio. Objetivo: Se propone un algoritmo neuronal de red de retropropagación (BP) para predecir la fatiga deportiva basándose en imágenes de señales de electromiografía (EMG). Métodos: El algoritmo de análisis de componentes principales se utiliza para reducir la dimensión de las características de la señal EMG. El ángulo de la articulación de la rodilla se estima mediante el algoritmo de la máquina de aprendizaje por encima del límite regularizado y el algoritmo de red neuronal BP. Resultados: el valor de RMSE del algoritmo de la máquina de aprendizaje por encima del límite regularizado es menor que el del algoritmo de red neuronal de BP. Al mismo tiempo, el valor ρ del algoritmo de la máquina de aprendizaje por encima del límite regularizado está más cerca de 1, lo que indica su mayor precisión. Conclusiones: El tiempo de entrenamiento del modelo del algoritmo de la máquina de aprendizaje por encima del límite regularizado se ha reducido en gran medida, lo que mejora la eficiencia. ***Nivel de evidencia II; Estudios terapéuticos: investigación de los resultados del tratamiento.***

Descriptores: *Ejercicio, alta intensidad; Fatiga; Articulación de la Rodilla.*

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INTRODUCTION

Statistics show that every year, more than 10 million people worldwide suffer from central or peripheral nerve damages due to cardio-cerebral vascular diseases and trauma, manifesting as motor dysfunctions of limbs[1]. Patients with limb motor dysfunction need not only medical treatment but also exercise rehabilitation training. Their sports limbs are prone to fatigue. Moderate fatigue is beneficial to the human body; however, excessive fatigue is likely to cause secondary damages and affect the rehabilitation effects. To make a timely and effective judgment and estimation of the fatigue status of patients during rehabilitation training, effectual detection methods are needed. However, it has not been solved yet. At present, the detection of sports fatigue mainly depends on biochemical indicators, behavior indicators, and physiological indicators. Among them, the biochemical indicators are complex and unstable, making it difficult to accurately detect sports fatigue with a certain indicator. Meanwhile, although the behavior indicators are easy to be realized, the detection effect is not ideal, and the recognized standard with effective persuasion is unavailable. The signals of physiological indicators are accurate, which can directly reflect the physiological changes in the human body. Especially, electromyography (EMG) signals have the advantages of convenient operation, non-invasiveness, and non-immersion in signal measurement; therefore, they have been widely applied in fatigue-related researches[2]. Zhou et al. (2018) used an over-limit learning machine algorithm to classify unknown electroencephalography (EEG) signals. The results showed that the algorithm was better than the support vector machine in terms of average training time and test accuracy, which had excellent generalization performances[3]. The over-limit learning machine algorithm has the advantages of fast training speed and good generalization performance. Studies have applied it to the classification of EEG signals, but few studies have applied it to fatigue detection of EMG signal images.

Therefore, in this study, the EMG signal images are used as physiological indicators. By continuously estimating the motion of the lower limb joints with the regularized over-limit learning machine algorithm and the back propagation (BP) neural network algorithm, an effective method for sports fatigue detection is provided.

METHODS

The over-limit learning machine algorithm included an input layer, a hidden layer, and an output layer. Each neuron in the same layer was not connected, but each neuron between two adjacent layers was connected. The input signal was represented by an input matrix, as shown in Equation (1).

$$\mathrm{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1Q} \\ x_{21} & x_{22} & \cdots & x_{2Q} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nQ} \end{bmatrix} \tag{1}$$

Where x_{11} to x_n represented the input signal, Q represented the length of the input data, and n represented the dimension of the input data.

The output signal was represented by an output matrix, as shown in Equation (2).

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1Q} \\ y_{21} & y_{22} & \cdots & y_{2Q} \\ \vdots & \vdots & & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mQ} \end{bmatrix} \tag{2}$$

Where y_{11} to y_n represented the output signal, Q represented the length of the output data, and m represented the dimension of the output data.

The weight of the input layer to the hidden layer was shown in Equation (3).

$$w = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2n} \\ \vdots & \vdots & \omega_{ji} & \vdots \\ \omega_{l1} & \omega_{l2} & \cdots & \omega_{ln} \end{bmatrix}_{l\times n} \tag{3}$$

Where ω_{ji} represented the weight from the input layer to the hidden layer.

The connection weight between the hidden layer and the output layer was obtained by the least square solution of Equation (4).

$$\min_{\beta} \left\| H^T \beta - Y' \right\| \tag{4}$$

Where Y' represented the transpose of Y, and β represented the connection weight from the hidden layer to the output layer. Therefore:

$$\hat{\beta} = H^T Y' \tag{5}$$

Where Y' represented the transpose of Y, and HT represented the generalized inverse matrix of the output matrix H.

Traditional over-limit learning machine algorithms were prone to overfitting, which affected the generalization performance. Therefore, this study introduced regularization coefficients in the solution, and improved the stability and generalization performance of the results through the regularization of over-limit learning machine algorithms. As shown in Equation(6):

$$\hat{\beta} = H^T \left(\frac{1}{C} + HH^T \right)^{-1} Y' \tag{6}$$

Where C represented the regularization coefficient.

First, the EMG features and knee joint angles were normalized. The regularized over-limit learning machine model was used for training. The 3 times cross method was used for verification. The number of hidden layers was set to 100, and the sigmoid function was used as the activation function of the hidden layers.

The BP neural network algorithm consisted of an input layer, a hidden layer, and an output layer. The input layer and the output layer were both fixed layers, and the hidden layer could be set as one to multiple layers. Neurons were not connected, but each neuron between two adjacent layers was connected. The error between the calculated value and the expected value of the network was shown in Equation (7):

$$E = \frac{1}{2}\sum_{k=1}^{n}\left\{ y_k - g\left[\sum_{j=1}^{l} \omega_{kj}^2 f\left(\sum_{i=1}^{m} \omega_{ij}^1 x_i - \theta_j^1 \right) - \theta_k^2 \right] \right\}^2 \tag{7}$$

Where g () represented the transfer function of the output layer, ω_{kj}^2 represented the weight between the hidden layer and the output layer, f () represented the transfer function of the hidden layer, ω_{ij}^1 represented the weight between the input layer and the hidden layer. θ^1 represented the hidden layer neuron threshold, and θ^2 represented the output layer neuron threshold.

The equation for calculating the weight between the input layer and the hidden layer was shown in Equation (8).

$$\omega_{ij}^1(t+1) = \omega_{ij}^1(t) - \eta^1 \frac{\partial E}{\partial \omega_{ij}^1} = \omega_{ij}^1(t) + \eta^1 \sigma_j^1 x_i \tag{8}$$

Where η^1 represented the learning step size of the hidden layer.

The equation for calculating the weight between the hidden layer and the output layer was shown in Equation (9).

$$\omega_{kj}^2(t+1) = \omega_{kj}^2(t) - \eta^2 \frac{\partial E}{\partial \omega_{kj}^2} = \omega_{kj}^2(t) + \eta^2 \sigma_j^2 O_j \quad (9)$$

Where η^2 indicated the learning step size of the output layer.

In general, a three-layered neural network could simulate various non-linear mappings. Therefore, this study used the BP neural network algorithm with one hidden layer. The unipolar sigmoid function was used as the activation function of the hidden layer The experimental data of 30 s were divided into 3 groups, and each group was 10 s. Next, two groups were selected in turn as training data, and the remaining group was calculated as test data.

Differences between features and methods were compared by calculating the Root Mean Square Error (RMSE) and Pearson correlation coefficient (denoted as ρ) as indicators.[4]

RESULTS

EMG signal image

The EMG signal image is shown in Figure 1. Due to the influence of sensors and the environment, the original EMG signal is mixed with noises. Thus, the original EMG signal is denoised and averaged by using a high-pass filter. Afterward, the output results are processed with a low-pass filter, and are then normalized. As shown in the processed EMG signal image, the influence of noise on the signal is reduced, and the signal-to-noise ratio of the surface EMG signal image is improved.

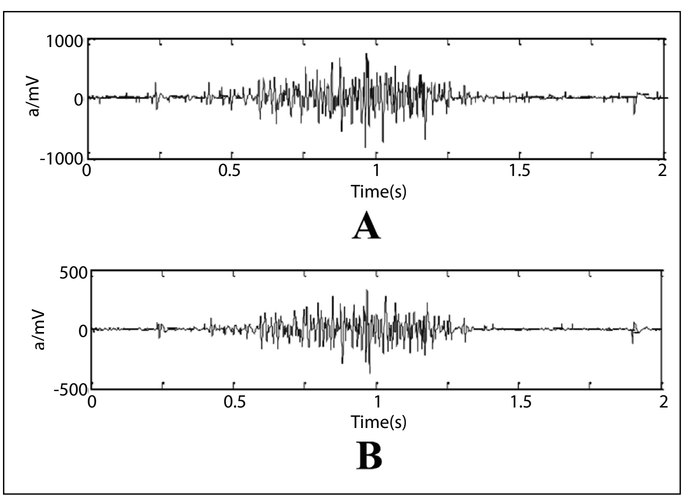

Figure 1. EMG signal image (A shows the original EMG signal image; B shows the processed EMG signal image).

Optimal EMG feature selection results

The single feature comparison and combined feature comparison of time-domain features are performed. The RMSE and ρ results are shown in Figure 2. As shown in the figure, when the single feature comparison of time-domain features is performed, the RMSE values are sorted in increasing order as follows: MAV, Log, WL, Var, and ZC. The ρ values are sorted in decreasing order as follows: MAV, Log, Var, WL, and ZC. Then, the first 4 single features with better effects are mutually combined (MAV, Log, WL, Var) as follows: MAV+Log, MAV+WL, MAV+Var, Log+WL, Log+Var, and WL+Var. These combinations are used as features to train the model. When combined feature comparison of time-domain features is performed, the RMSE values are sorted in increasing order as follows: MAV+Log, MAV+WL, MAV+Var, Log+WL, Log+Var, WL+Var. The ρ values are sorted in decreasing order as follows: MAV+Log, MAV+WL, MAV+Var, Log+WL, Log+Var, WL+Var. Therefore, the optimal EMG feature should be MAV+Log.

Comparison results between regularized over-limit learning machine algorithm and BP neural network algorithm

The comparison results between the regularized over-limit learning machine algorithm and the BP neural network algorithm are shown in Figure 3.

The comparison results of the two algorithms are shown in Table 1. As shown in the table, under both the knee flexion and extension mode and the deep squat mode, compared with the BP neural network algorithm, the RMSE value of the regularized over-limit learning machine algorithm is lower. Also, its ρ value is closer to 1, which indicates that the prediction accuracy of the regularized over-limit learning machine algorithm is higher. Meanwhile, its model training time has been greatly reduced.

DISCUSSION

Research on EMG signals has gradually become a focus in the fields of rehabilitation medicine and biomechanics. Du et al. (2018) used fuzzy approximate entropy and complexity algorithms to calculate the corresponding muscle fatigue indicators, and utilized the least-squares method to calculate the relative determination coefficient of the linear regression of the muscle fatigue scale. The results showed that fuzzy approximate entropy could be used as a better evaluation algorithm to evaluate neck muscle fatigue.[5] This study collects the data of the EMG signal image, preprocesses the EMG signal image, selects 5 time-domain

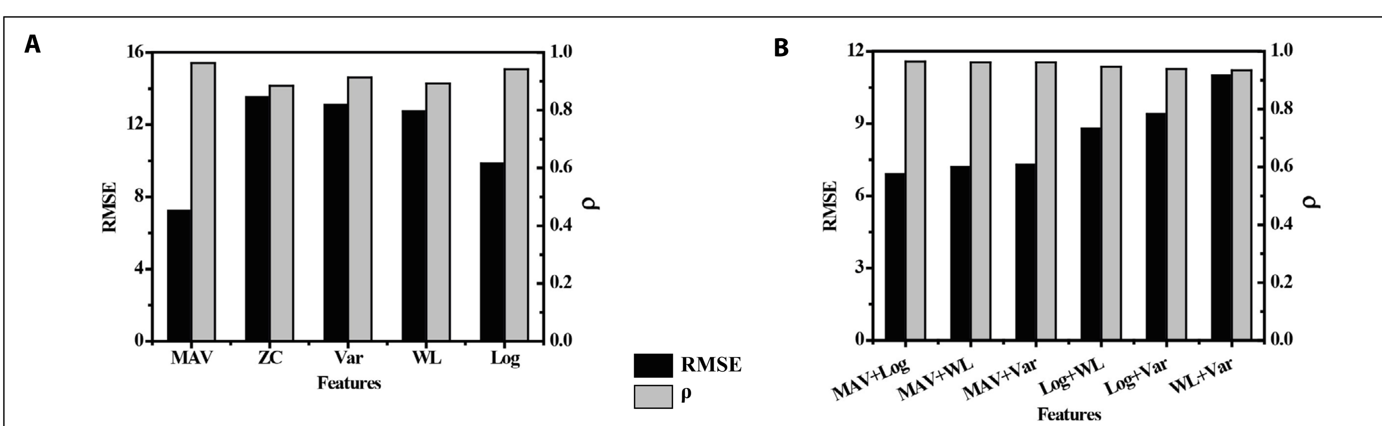

Figure 2. Comparison results of single feature and combined feature of time-domain features (A shows the comparison of single feature; B shows the comparison of combined feature).

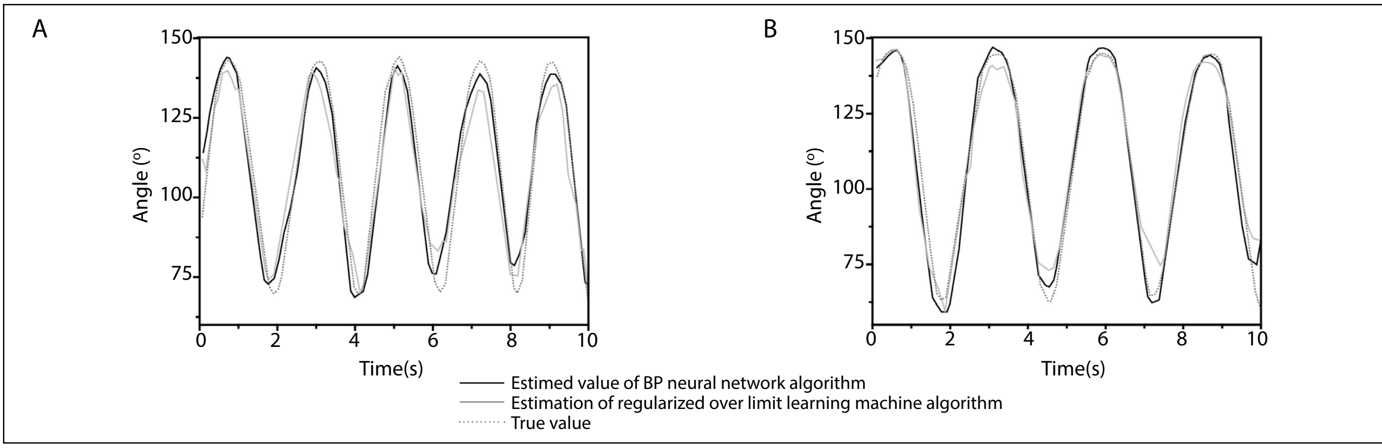

Figure 3. Comparison results of regularized over-limit learning machine algorithm and BP neural network algorithm (A shows the result of the indicator prediction model under the knee flexion and extension mode; B shows the result of the indicator prediction model under the squat mode).

Table 1. Comparison results of the two algorithms.

Motion modes	Prediction results	Regularized over-limit learning machine algorithm	BP neural network algorithm
Knee flexion and extension mode	RMSE	8.542	9.320
	ρ	0.966	0.941
	Model training time	0.024	2.673
Deep squat mode	RMSE	5.116	5.695
	ρ	0.978	0.969
	Model training time	0.028	2.714

features of MAV, ZC, Var, WL, and Log, and finds the best EMG feature by comparing the single feature and the combined feature. The results show that the optimal EMG feature combination is MAV+Log. Zhang et al. (2017) used principal component analysis and independent component analysis to decompose the EMG signals, and utilized the artificial neural network algorithm to estimate the angle of the upper limb joints. The results showed that using independent component analysis combined with an artificial neural network algorithm was feasible and effective for joint kinematics estimation.[6] In this study, the principal component analysis algorithm is used to reduce the feature dimension of EMG signals. The knee joint angle is estimated by the regularized over-limit learning machine algorithm and the BP neural network algorithm. The results show that under both the knee flexion and extension mode and the deep squat mode, compared with the BP neural network algorithm, the estimated value of the regularized over-limit learning machine algorithm is closer to the true value, and the model is more stable. The RMSE value of the regularized over-limiting learning machine algorithm is lower than that of the BP neural network algorithm. Meanwhile, the ρ value of the regularized over-limit learning machine algorithm is closer to 1, which indicates that the regularization of the over-limiting learning machine algorithm has higher prediction accuracy. Compared with the BP neural network algorithm, the model training time of the regularized over-limit learning machine algorithm has been greatly reduced, which improves the efficiency.

CONCLUSION

This study collects the data of the EMG signal, preprocesses the EMG signal image, selects the time-domain feature to find the optimal EMG feature, and uses the principal component analysis algorithm to reduce the feature dimension of the EMG signal. The regularized over-limit learning machine algorithm and BP neural network algorithm are used to estimate the knee joint angles. The results show that compared with the BP neural network algorithm, the regularized over-limit learning machine algorithm has higher model stability and prediction accuracy. Meanwhile, its model training time has been greatly reduced, which improves its efficiency. Therefore, the regularized over-limit learning machine algorithm has advantages in accuracy and real-time prediction, which has application values in improving sports fatigue indicators. This study provides guidance for sports fatigue estimation and has certain theoretical and practical significance. However, the research on the prediction model of sports fatigue in this study is still in the initial stage of the trial. There are also some deficiencies in the research process. For example, the selected subjects are only healthy volunteers. In the later research process, all groups will be included, including the trials in patients who have difficulties in exercising. Therefore, the obtained results will be more valuable.

All authors declare no potential conflict of interest related to this article

AUTHORS' CONTRIBUTIONS: Xiaoli Wang collated all the experimental data. Chunmin Dai was a major contributor in writing the manuscript.

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