Application of PCA-LSTM model in human behavior recognition

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Abstract. For the problem that the recognition rate of human upper extremity movements is not high and existing models are prone to "dimensional disaster", a pattern recognition algorithm based on PCA-LSTM neural network is studied. Collect and process the surface electromyography signal (sEMG) of the human upper limbs, and put it into the PCA model for data dimensionality reduction, put the dimensionality-reduced data into the LSTM neural network model to classify the human behavior, count the classification efficiency and recognition rate. Comparing PCA-LSTM with the traditional classification algorithm SVM and random forest, the calculation efficiency is improved by 31% and 53%, the recognition rate is increased by 3.9% and 4.6% and the classification effect is significant.

Keywords: sEMG, PCA-LSTM, Dimensionality reduction, Pattern recognition.

1. Introduction
Upper limb motion recognition is an important part of human behavior recognition. In recent years, research at home and abroad has made some progress. Domestic and foreign scholars have widely used classification methods such as SVM algorithm and random forest algorithm to perform pattern recognition on EMG signals [1]-[3], so as to determine the type of related actions, which is good for the clinical application of EMG pattern recognition. At the same time, it is worthy of our attention that the existing EMG signal classification algorithm still has the problem of "dimensional disaster" caused by excessive data dimensionality. At the same time, there is a problem of relatively low recognition rate.

This paper designs a model for EMG signal recognition based on PCA-LSTM, imports EMG signals collected by EMG signal acquisition instrument into PCA algorithm, and uses PCA algorithm to perform principal component analysis on experimental data. At the same time, the dimensionality reduction operation is completed, which greatly reduces the impact of the "dimensional disaster". Using the LSTM neural network as a classifier, the classification results are marked. The data is imported into the LSTM neural network to optimize the LSTM parameters, train a specific mathematical model suitable for upper limb movement pattern recognition, and use the test set for experimental verification.
2. Experimental data collection and preprocessing
The experiment completed four movements, make a fist, open hand, wrist flexion and lifting. The corresponding main muscles include the ulnar carpal flexor, superficial flexor, Palmaris longus and extensor digit rum. In the experiment, a patch-type bio electrode and a surface EMG collector were used to collect EMG signals. The sampling frequency was 1000 Hz, and the collected EMG signals were passed through a low-pass filter at 2000 Hz, a high-pass filter at 10 Hz, and a power frequency notch at 50 Hz.

After the EMG signal is filtered, the eigenvalues are calculated. The eigenvalues are the root mean square (RMS) in the time domain, the median frequency (MF) in the frequency domain, the third-order wavelet packet coefficients in the time-frequency domain have the largest variance value (Emm) and the maximum value of wavelet packet coefficient energy (VARmm) are used as the characteristic values.

3. PCA algorithm
PCA, principal component analysis, is a commonly used data dimensionality reduction method [4]. It can transform the original data into a set of linearly independent representations of various dimensions through linear transformation to extract the main linear components of the data. Its function is expressed as:

$$z = w^T x$$

(1)

In the formula, $z$ is a low-dimensional matrix, $x$ is a high-dimensional matrix, and $w$ is the mapping relationship between the two.

It can be seen from equation (1) that the most important component is such $w_1$, and the projection of the sample onto $w_1$ is most dispersed, making the difference between the samples very obvious. In order to get the only solution and this direction becomes the most important factor, we need to find $w_1$, maximize $w_1$ under constraints, and write it as a Varangian problem. Derivation of $w_1$ makes it 0:

$$2\sum w_i - 2\alpha w_1 = 0$$

(2)

In order to maximize the variance, we select the eigenvector with the largest eigenvalue, complete the principal component analysis, and reduce the dimension of the data.

4. LSTM neural network

LSTM, the long-term and short-term memory network, is a special kind of RNN that can learn long-term dependencies [5]. As shown in Figure 1, there are four neural network layers in the repeating
module of LSTM, and there is a very special way of interaction between them. The key to LSTM is the cell state, which is the horizontal line across the top of the entire cell in Figure 2.

![Cell State of LSTM](image)

The first step in LSTM is to decide what information to discard from the cell state. This decision is made by forgetting the gate layer. The structure is shown in Figure 3, and the function is expressed as Equation 3:

\[ f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \]  

The next step is to determine what new information is stored in the cell state. There are two parts here. First, the sigmoid layer, the "input gate layer", determines what values will be updated. Then, a new candidate value vector is created by the tanh layer. The structure is shown in Figure 4, and the function is expressed as Equation 4-5:
After updating the time of the old cell state, the final output is determined based on the cell state. Create an output gate of the sigmoid layer to determine which parts of the cell will be output. Then we multiply the cell state through tanh (so that the output value is between -1 and 1) and multiply it by the output gate to get the final output result. The structure is shown in Figure 5, and the function is expressed as Equation 6-7:

\[ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \]  
\[ C_t = \tanh(W_c [h_{t-1}, x_t] + b_c) \]

5. Experiments and results
The test subjects included 3 males: aged 23 to 25 years old, weighing 55 to 75 kg, and a height of 160 to 181 cm; 3 female: aged 23 to 25 years old, weighing 42 to 54 kg, and a height of 152 to 175 cm. After conducting experimental data collection and preprocessing on them, they were input into the PCA-
LSTM model for calculation. After averaging, the recognition rate and efficiency of pattern recognition were obtained. Compared with the SVM algorithm and the random forest algorithm, the experimental results are shown in Table 1:

| algorithm      | Recognition rate | Recognition efficiency |
|----------------|------------------|------------------------|
| PLA-LSTM       | 96.8%            | 100%                   |
| SVM            | 92.9%            | 69%                    |
| Random forest  | 92.2%            | 47%                    |

The recognition efficiency in the table is based on the PCA-LSTM algorithm, and the reciprocal of the running time of the algorithm is used as the calculation method.

6. Conclusions
This paper presents a pattern recognition algorithm for EMG signal based on PCA-LSTM model, and compares it with SVM and random forest algorithm. It is found that the PCA-LSTM algorithm has relative advantages in terms of recognition rate and recognition efficiency. It solves the "dimensional disaster" problem and improves the recognition rate of EMG signals, which lays an experimental foundation for the practical application of the algorithm model.

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