LVQ Neural Network Applied for Upper Limb Motion Recognition for Home-based Stroke Rehabilitation

Lei Yu, Liquan Guo, Xudong Gu, Jianming Fu, and Qiang Fang

***Abstract*—To improve the rehabilitation effectiveness and reduce the hospital costs, a new upper limb motion recognition model, through which hospital based clinicians can remotely supervise home based stroke rehabilitation, is proposed in this paper. Firstly, the real time limb motion data is collected using a 3-axis accelerometer sensor which is fixed on the upper limb of a patient. Secondly, the Wavelet Transform is employed to extract the approximation coefficients of different types of rehabilitation motions. Finally, a recognition model is established based on an LVQ neural network. 2 typical rehabilitation motions, Bobath handshaking and wrist turning, were chosen to test this proposed recognition system. The experiment results indicate that the recognition accurate rate can achieve as high as 100%. This pilot forms a foundation to further develop a home based remote training and assessment system for stroke rehabilitation.**

I. INTRODUCTION

With the change of people's life style, cerebrovascular diseases have become a major cause of people's death and disability worldwide. According to an incomplete statistics, there are about 1.5 million patients died from stroke each year in China, and there are more than 2 million new stroke patients each year. The healthcare expenditure for these stroke patients is about 20 billion Chinese Yuan each year [1].

For the past decades, many research efforts have been spent on finding an effective method to improve the rehabilitation effectiveness and reduce the hospital costs. Nowadays, several rehabilitation robotic systems have been commercialized and put into clinical use to replace the traditional rehabilitation approach which is quite labor intensive. Among those are the InMotion System developed by Interactive Motion Technologies Inc, Manus System developed by MIT [2], Armeo System developed by Hocoma Inc [3], ReoGo System developed by ReoTherapy Inc [4], and so on.

However, there are some shortcomings associated to those robotic systems. Firstly, these robotic systems are all developed for hospitals and large rehabilitation center, which will cause inconvenience to discharged patients and their family members. Secondly, the hospital costs are so high that many families cannot afford.

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Considering the above facts, this paper proposes a new upper limb motion recognition model, through which clinicians in hospital can remotely recognize what types of motion the patients have practiced at home. Three steps are involved in this approach. At first, the real time motion data is collected by using a 3-axis accelerometer sensor which is fixed on the upper limb of a patient. Then the approximation coefficients of different rehabilitation motions are calculated using Wavelet Transform. Finally, the recognition model based on LVQ neural network is established.

The rest of the paper is organized as follows. In Section Ⅱ, the principle of Wavelet Transform data compression and LVQ neural network modeling will be presented. The experiments and results will be discussed in Section Ⅲ and Section Ⅳ respectively. Finally the paper is concluded in Section Ⅴ.

II. METHODOLOGY

A. Data Compression using Wavelet Transform

In order to establish the motion recognition model rapidly and accurately, it is needed to preprocess the raw rehabilitation motion signals, extract the features, and take them as the input of recognition model.

In technical literature, there exists a large number of feature extracting techniques, among them methods based on wavelet transform compression are well known and successfully applied in many fields. The principle of wavelet transform [5] is described as follows.

Similar to the generalized Fourier series expansion, the time-domain signal $x(t)$ can be expanded in terms of a weighted sum of a set of basis functions using wavelet transform. While for the classical Fourier series the basis functions are sine and cosine functions at different frequencies, in the case of wavelet series, the basis functions $\psi_{jk}(t)$ are translations and dilations of a signal fixed function $\psi(t)$ called the mother wavelet.

$$\psi_{jk}(t) = 2^{j/2}\psi\left(2^{j}t - k\right), j,k \in Z \tag{1}$$

For certain choices of $\psi(t)$, the corresponding set of

$\psi_{jk}(t)$ forms an orthonormal basis in $L^2(R)$. In this case,

$$x(t)=\sum_j \sum_k d_{jk}\psi_{jk}(t) \tag{2}$$

where the wavelet coefficients d_{jk} are calculated using the relation

$$d_{jk}=\int x(t)\psi_{jk}(t)\,dt=2^{j/2}\int x(t)\psi\left(2^j t-k\right)dt \tag{3}$$

In contrast to the sines and cosines, wavelets are local in frequency/scale via dialations and in time via translations. This localization offers an advantage, since fewer wavelet basis functions are usually needed to represent the signal $x(t)$ to a given level of approximation. This property is of great importance in the compression of the signal.

The procedure to compress any signal $x(t)$ using wavelet transform method involves three steps: preprocessing, wavelet decomposition, and thresholding [5]. Due to the careful representation by wavelets, it is reasonable to assume that only a few coefficients contain information about the real signal while others appear as less important details. The goal is to extract these significant coefficients and to ignore others.

Meanwhile, considering the fact that the noisy signal caused by patient's shaking during measurement is so small that can be ignored, and the procedure of data compression in this paper simply includes two steps: preprocessing and wavelet decomposition. After wavelet decomposition, the approximation coefficients are selected as the input of the motion recognition model.

In data compression, it is desired to represent data by as small as possible number of coefficients within an acceptable loss of visual quality. Therefore, there must be some evaluation indices to evaluate the difference between the reconstructed signal and the raw signal. In this paper, Energy Packing Efficiencies (EPE) is used as the evaluation index, which is defined as the ratio of the energy captured by the approximation coefficients and the energy captured by the whole number of coefficients.

$$EPE=\frac{\sum_{n=1}^{M}\left(c(n)\right)^2}{\sum_{n=1}^{L}\left(c(n)\right)^2}\times 100 \tag{4}$$

where M and L are the number of approximation coefficients and the whole number of coefficients, respectively [5].

Generally speaking, if the energy captured by the approximation coefficients is more than 98% of the total energy, in other words, if EPE > 98, then it is deemed that the difference between the reconstructed signal and the raw signal is so little that can be ignored.

B. Motion Recognition Model based on LVQ Neural Network

After extracting the approximation coefficients of rehabilitation motions, the next task of this paper is to establish the motion recognition model based on Learning Vector Quantization (LVQ) neural network.

As a supervised method, LVQ uses known target output classifications for each input pattern of the form. The architecture of LVQ neural network is shown in Fig. 1. Different from traditional single-hidden layer feedforward networks (SLFNs), the neurons in compete layer are partially connected to the neurons in output layer. That means, each neuron in compete layer is only connected to one neuron in output layer, and conversely, each neuron in output layer can connect to many neurons in compete layer.

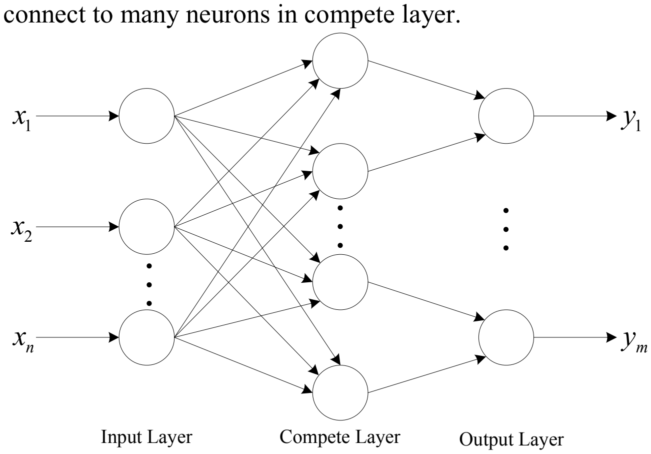

Fig. 1. The architecture of LVQ neural network.

The basic procedure of LVQ algorithm is described as follows:

Step1: Initialize the connect weight between input layer and compete layer, which is denoted by $\mathbf{W}$.

Step2: Calculate the Euclidean distance between the input vector $\mathbf{X}$ and each neuron in compete layer, respectively.

Step3: Find the "winner" neuron in compete layer which has the shortest distance according to Step2, then search the neuron in output layer which is connected to the "winner" neuron.

Step4: If the label of the searched neuron is equal to the target label of input vector, regulate the connection weight of "winner" neuron according to Eq. 5, otherwise, regulate the connection weight of "winner" neuron according to Eq. 6.

$$\bar{\mathbf{w}}_i=\mathbf{w}_i+\eta\left(\mathbf{x}-\mathbf{w}_i\right) \tag{5}$$

$$\bar{\mathbf{w}}_i=\mathbf{w}_i-\eta\left(\mathbf{x}-\mathbf{w}_i\right) \tag{6}$$

where $\bar{\mathbf{w}}_i$ represent the connection weight of "winner" neuron after regulation; $\mathbf{w}_i$ represent the connection weight of "winner" neuron before regulation; η ($\eta>0$) represents the learning rate.

Because LVQ neural network not only has the advantages of traditional supervised neural networks (like BP, RBF neural network, etc), but also has the advantages of unsupervised neural networks (such as compete, SOM, etc), it has been successfully applied to pattern recognition, multi-class classification and data compression tasks, e.g. speech recognition, image processing or customer classification.

Additionally, there is no necessary to normalize or orthogonalize the raw signal; therefore it is convenient for users to establish classifiers by using LVQ neural network.

III. EXPERIMENT

A. Data Sampling

The data sampling task of 2 typical rehabilitation motions (Bobath handshaking and wrist turning) was finished at Rehabilitation Medical Center of The Second Hospital of Jiaxing, Zhejiang Province, China.

For the above 2 typical rehabilitation motions, the position of 3-axis accelerometer sensor is different. While gathering the upper limb motion data of Bobath handshaking, the 3-axis accelerometer sensor is fixed on the biceps; and while gathering the motion data of wrist turning, the 3-axis accelerometer sensor is fixed on the wrist. The sampling results are shown in Fig. 2, and Fig. 3, respectively.

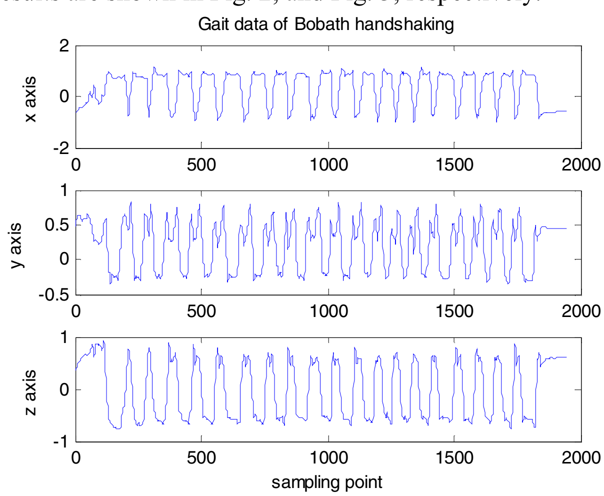

Fig. 2. Real time motion data of Bobath handshaking.

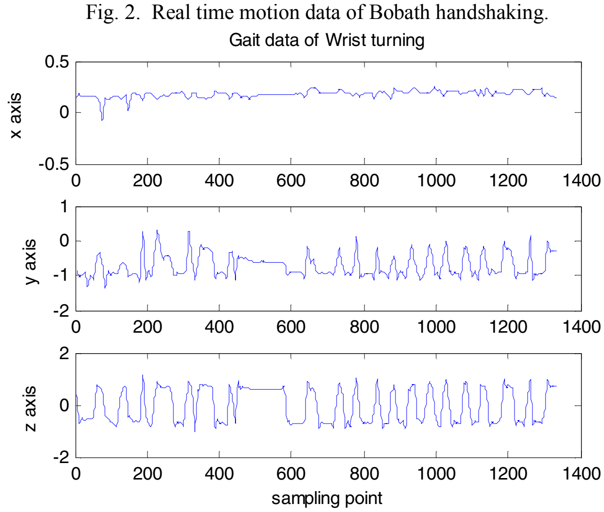

Fig. 3. Real time motion data of Wrist turning.

B. Approximation Coefficients Extracting

Based on the data compression method described in Section Ⅱ, this paper selected Daubechies 3 wavelet as the mother wavelet, and did a 3-scale decomposition.

Considering the duration of 2 different rehabilitation motions are not equal, here we interpolated the raw signal to make sure that each cycle of 2 different rehabilitation motions has same number of data points. Fig. 4 describes the wavelet transform results of a cycle of Bobath handshaking motion, which include 60 data points.

Table I lists the corresponding EPE of approximation coefficients and detail coefficients, respectively. As defined in Eq. 4, the EPE of detail coefficients represent the ratio of the energy captured by the detail coefficients in each scale and the energy captured by the whole number of coefficients. It is easy to find that the EPE of approximation coefficients is 99.66, which means the 11 approximation coefficients can represent the original signal almost perfectly.

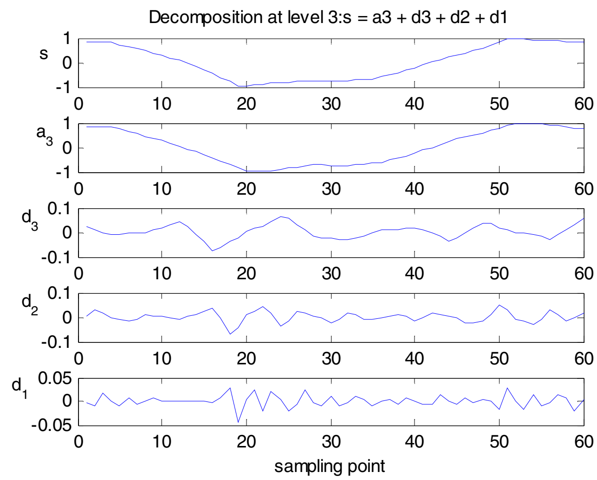

Fig. 4. Wavelet transform results of a cycle of Bobath handshaking motion

TABLE I

EPE OF A CYCLE OF BOBATH HANDSHAKING MOTION

	Approximations	Details		
	A_3	D_3	D_2	D_1
Energy	48.0872	0.1280	0.0258	0.0095
EPE	99.66	0.27	0.0005	0.0002
Number of coefficients	11	11	18	32

C. Motion Recognition Model Establishing

As shown in Fig. 3, the change of x-axis is not obvious, so in this paper, we select the z-axis gait data as the original data.

The first step of establishing the motion recognition model is to define the structure of LVQ neural network. In other words, we must answer the following two questions. 1) How many neurons are required in the input layer and in the output layer? 2) How many neurons are required in the compete layer?

By using the interpolation method, the number of sampling points of each rehabilitation motions is equalized to 60. Then 11 approximation coefficients were extracted and taken as the input vector of the LVQ neural network. Meanwhile, the number of neurons in compete layer is set to 5 to construct an 11-5-2 LVQ neural network.

The second step of establishing the motion recognition model is to determine the size of training set and testing set. 15 cycles of motion data were selected for each Bobath handshaking and wrist turning as the training data set, and the remaining 5 cycles of motion data were used as the testing set for each motion. To evaluate the performance of the constructed motion recognition model, the recognition accuracy is used as the criterion.

IV. Results and Discussion

A. Experiment Results

The prediction results of the testing set are listed in Table Ⅱ, from which it is clear that the motion recognition model based on the LVQ neural network can accurately classify both the Bobath handshaking and the wrist turning motions.

TABLE Ⅱ
PREDICTION RESULTS OF TESTING SET

Sample number	True motion	Predict motion	Sample number	True motion	Predict motion
1	Bobath	Bobath	6	wrist	wrist
2	Bobath	Bobath	7	wrist	wrist
3	Bobath	Bobath	8	wrist	wrist
4	Bobath	Bobath	9	wrist	wrist
5	Bobath	Bobath	10	wrist	wrist

B. Discussion

According to the experiment results, it can be concluded that the method proposed in this paper is a successful attempt to recognize stroke patients' rehabilitation motions without clinician's onsite supervision, and this is a very important technique in the future home-based rehabilitation.

However, there is a strong assumption in data compression process, which assumes the noisy signal caused by the patient's body shaking is so small that can be ignored. Actually, to the seriously ill stroke patients, the amplitude of random shaking is too big to ignore. Therefore, besides the approximation coefficients, some detail coefficients are also needed to fully represent the original rehabilitation motions. Consequently, the thresholding process of detail coefficients is another essential task that needs to be solved.

V. Conclusion

In order to help stroke patients perform rehabilitation at home, this paper proposes a new upper limb motion recognition model using wavelet transform based compression and an LVQ neural network. By using this model, clinicians in hospital can remotely recognize what types of rehabilitation motions the home based stroke patients have done without onsite supervision. The experiment results indicate that the proposed method can recognition the rehabilitation motions perfectly, and thus form a solid foundation for the further development of a home based stroke rehabilitation training and assessment system. For the future work, there are some important issues need to be addressed. Those issues include the recognition of other typical and common rehabilitation motions and the evaluation of the quality of patient's rehabilitation motions.

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