Upper Limb Motion Recognition for Unsupervised Stroke Rehabilitation Based on Support Vector Machine

Liquan Guo, Lei Yu, Qiang Fang

***Abstract*—In order to monitor the rehabilitation training of stroke patients in unsupervised situation and provide rehabilitation advice for rehabilitation clinicians, a wireless upper limb motion recognition system has been developed using tilt sensors, to identify the complex upper limb movements such as flexion and extension of elbow, flexion of elbow and touch the head, from a stroke patient's rehabilitation program. 18 different movements from a stroke patient's rehabilitation training program were adopted to verify and validate this system with 12 of them in the training group and 6 of them in the testing group. After preprocessing and the feature extraction of the acquired motion data, the Support Vector Machine (SVM) recognition approach was employed to establish a small sample identification model. Finally, the data of testing group in the upper limb rehabilitation training program were used to identify the developed model. It has been found that the recognition accuracy from this developed model was 100%. This result provides a well reference for further development of an automated system for stroke patient rehabilitation motion recognition.**

I. Introduction

Nowadays, with the improvement of people's living standard and the rapid aging of population in many countries, stroke has become a leading cause of death and ongoing disability in the world. 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]. On the other hand, in most developing countries, there is no enough rehabilitation centers or other rehabilitation institutions for treating stroke patients. At the same time, the healthcare expenditure dedicated to stroke related diseases is becoming higher and higher which is out of the affordability of many families. Therefore, many current researches have been focused on developing unsupervised rehabilitation methods which enable the patients to perform scheduled rehabilitation training outside medical facilities. For stroke patients, one major problem to be solved in this research is to find a reliable continuous monitoring method that can provide real-time feedback of patient's training progress to the responsible medical professionals and at the same time ensure the patient's safety [2].

Manuscript received July 10, 2011.

Liquan Guo is with Suzhou Institute of Biomedical Engineering and Technology, CAS, China (e-mail: guolq@sibet.ac.cn).

Lei Yu is with Suzhou Institute of Biomedical Engineering and Technology, CAS, China (e-mail: yul@sibet.ac.cn).

Qiang Fang is with Suzhou Institute of Biomedical Engineering and Technology, CAS, China (corresponding author to provide phone: +86-512-69588240; fax: +86-512-69588255; e-mail: qfang@ sibet.ac.cn).

During the rehabilitation process, a patient's motion is one of the most difficult tasks to be recorded. At present, the common human motion-capturing methods are visual based tracking systems which utilize optical sensors and visual markers to track the body movements. Visual based tracking systems provide higher standard accuracy in general. However, the systems using visual markers may experience occlusion problem which means these systems will have a problem capturing the movements that involves body overlapping and joint rotating while these movements can commonly be found in rehabilitation training exercises [3,4]. Visual based systems are also relatively heavy, costly, and difficult to set up or calibrate which make it not suitable for home-based application.

According to that, this paper presents a wireless tilt sensor based motion tracking system, which consists of two tilt sensors and a receiver module. The tilt sensors have digitized outputs and needn't complex external circuitry. Therefore, the proposed design is much more compact than other conventional systems. Due to its low-power design, the system can work continuously two hours per day for more than one week time, which make the system very suitable for the application of unsupervised home rehabilitation monitoring. Additionally, due to its low cost and friendly usability, the system can provide safety measures such as fall detection for elderly people.

The rest of the paper is organized as follows. In Section II, the system architecture will be presented, including the general outline, the hardware design and the SVM model. The detailed experiment design such as data sampling and preprocessing, feature extraction motion recognition model base on SVM will be explained in Section III and the results and the future work will be discussed in Section IV respectively. Finally, the paper will be concluded in section V.

II. System Description

A. General Description

During the rehabilitation training progress, the training data is collected by a set of tilt sensors, sent to the receive module wirelessly, and then sent to a PC via a USB or RS232 interface. On the PC, the raw data is stored on the hard disk and displayed on the screen. The patients can then watch their real time training motions. After preprocessing, the training data is then sent to the motion recognition classifier to identify which actual movement the patient just did. The identified result is sent to the server in hospital via internet for clinician's perusal. The rehabilitation specialists can then view and analyze the patients' training quality and the current impairment condition from the uploaded patients' body and limb movement data on the server, and provide advice and decision on patient's next training session. The system architecture is illustrated in Fig. 1.

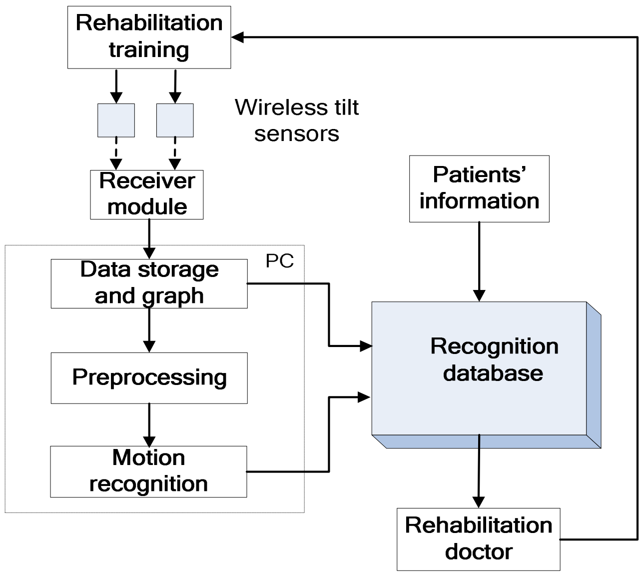

Fig. 1 The scheme of motion tracking system.

B. Hardware

The hardware system consists of two wireless tilt sensors and one receiver module connected to a PC via a RS232 port. Each sensor node consists of a low-power ZigBee MCU and a 3-D accelerometer with digital output via an SPI interface. With a total current of 28mA, the sensor can work continuously two hours a day for at least one week. Two sensor nodes were attached to the patient's left arm on the wrist and above the biceps for the upper limb movement monitoring.

The receiver module also contains a low-power ZigBee MCU, supported by the protocol stack of ZigBee2006 and ZigBee2007, which are both based on IEEE 802.15.4. As a result, the network construction is a simple and easy process.

The output of tilt sensors is already in its digital form, including the gravity component of x-axis, y-axis and z-axis, which can reflect the motion track and tilt level of the object that the sensors attached. A custom data protocol and format is designed. When the system is operating, the MCU of the receiver module sends out an address command every 10ms for node selection. Both tilt sensors compare the address with their own addresses. Only the tilt sensor whose address is in agreement with the address sent from the receiver sends its data to the ZigBee receiver. So for each sensor, the total data acquisition time is 20ms, i.e., in every second it sends 50 packets of data to PC through the receiver module. This data transmission rate is enough for rehabilitation training purpose.

C. SVM Model

After the limb motion data are gathered from the tilt sensors, the next important task is to establish the motion recognition model. Considering the experiments in Section III including 18 periods of motions, a motion recognition model was established here by using SVM method because SVM can achieve better generalization with a small set of training samples [5], compared with other traditional supervised and unsupervised neural network based techniques. The following is a basic introduction of SVM [6, 7].

Given training vectors $x_i \in R^n, i = 1, \ldots, l$, in two classes, and a vector $y \in R^l$ such that $y_i \in \{1, -1\}$. The goal is to find a hyperplane which can classify these two classes correctly.

Suppose the hyperplane is described by

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \tag{1}$$

Consequently, the above classification problem can be write as

$$\begin{cases} \mathbf{w} \cdot \mathbf{x}_i + b \ge 1, & y_i = 1 \\ \mathbf{w} \cdot \mathbf{x}_i + b \le -1, & y_i = -1 \end{cases} \qquad i = 1, \ldots, l \tag{2}$$

Theoretically, there may exist infinite hyperplanes satisfy (2), the task of SVM is to find the best hyperplane which is the farthest one from the training set. Mathematically, the above problem is to solve the following optimization problem

$$\begin{aligned} & \min_{\mathbf{w}, b, \xi} \quad \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \sum_{i=1}^{l} \xi_i \\ & \textit{subject to} \quad y_i \left(\mathbf{w}^T \phi(\mathbf{x}_i) + b \right) \ge 1 - \xi_i \\ & \qquad \xi_i \ge 0, i = 1, \ldots, l \end{aligned} \tag{3}$$

Its dual is

$$\begin{aligned} & \min_{\boldsymbol{\alpha}} \quad \frac{1}{2} \boldsymbol{\alpha}^T Q \boldsymbol{\alpha} - \mathbf{e}^T \boldsymbol{\alpha} \\ & \textit{subject to} \quad y^T \alpha = 0 \\ & \qquad 0 \le \alpha_i \le C, i = 1, \ldots l \end{aligned} \tag{4}$$

where $\mathbf{e}$ is the vector of all ones, $C > 0$ is the upper bound, Q is an l by l positive semidefinite matrix

$$Q_{ij} = y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \tag{5}$$

and $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ is the kernel.

The decision function is

$$\operatorname{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b \right) \tag{6}$$

After the model is trained by solving the above optimization problems, users can predict labels of testing data. Generally, we can evaluate the predictions by the following measures.

$$Accuracy = \frac{\#correctly\ predicted\ data}{\#total\ data} \times 100\% \tag{7}$$

III. EXPERIMENTS

A. Data Sampling and Preprocessing

In order to examine the performance of the proposed system, an experiment involved in one 76 years old female stroke patients was carried out. Several typical rehabilitation movements, such as the flexion and extension of elbow (abbreviation elbow motion), and the flexion of elbow and touch the head (abbreviation elbow head motion) were used in the experiment. For each motion, 18 repetitive exercises done by this stroke patient were used to verify and validate the developed recognition system with 12 of them in the training group and the other 6 in the testing group respectively. The patients were asked to repetitively perform these common upper limb exercises with wireless inertia sensors attached to their arms. The exercises were sampled under relatively loose supervision, which means the movements recorded were performed at various speed and completeness, in order to simulate the real practice situation.

In this presented pilot work two different typical training exercises, the elbow motion and the elbow head motion, were selected. These two motions are relatively complex than other motions such as Bobath handshaking and wrist turning and need 2 tilt sensors at the same time to perform the recognition task.

For each motion, the patient was asked to repeat 18 times, according to the rehabilitation clinician's suggestion. The motion tracking system operates in a period of 30 to 50 seconds, according to the physical condition of the patient. During the whole data acquisition process, all the training exercises of the patients were guided by a rehabilitation doctor. Therefore, the raw data were accord with the real practice situations.

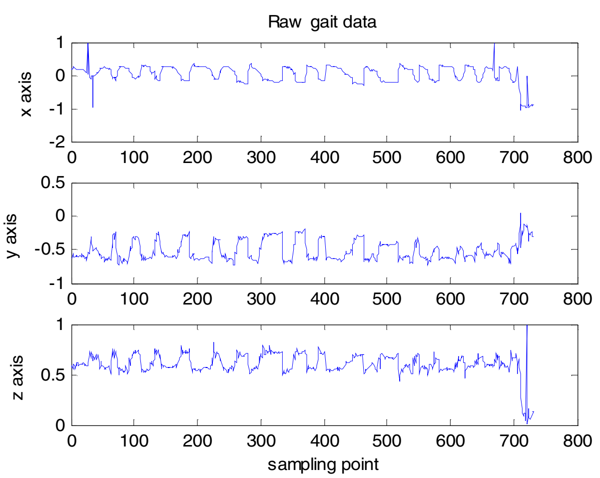

Fig. 2 The raw data gathered from a patient's upper limb while doing elbow motion.

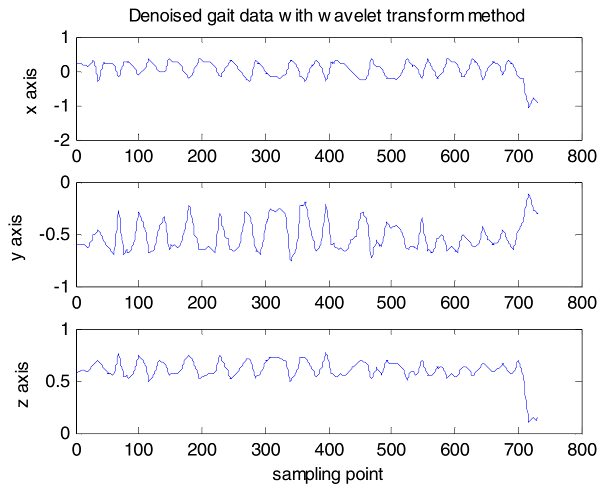

Fig. 3 The denoised patient upper limb motion data using wavelet transform denoising method.

Fig. 2 shows the upper limb movement data gathered from one of the 3-axis tilt sensors while the patient doing the elbow motion. It is obvious that the raw signal contains noise caused by the patient's random shaking and other irrelevant motion components. By using wavelet transform decomposition and then thresholding the detail coefficients of each scale, the noise in raw signal can be suppressed nicely. Fig. 3 shows the denoised data from which it can be seen that the signal is smoother after preprocessing.

B. Feature Extraction

Considering the number of sampling points in each period is about 60, we can't take all the sampling points as the input attributes of the motion recognition model, therefore it is quite necessary to extract some features as the input attributes. In this pilot study, total 12 attributes, 6 attributes from each tilt sensor were extracted and used. They are the initial position and amplitude of x, y and z axis respectively.

Table Ⅰ and Table Ⅱ list the above 12 attributes of one period of patient's elbow motion and elbow head motion respectively.

TABLE Ⅰ
12 ATTRIBUTES OF ONE PERIOD OF THE PATIENT'S ELBOW MOTION

Attributes	Values of Sensor 1	Values of Sensor 2
Initial x-axis position	0.22	-1.01
Initial y-axis position	-0.61	-0.35
Initial z-axis position	0.57	0.08
x-axis amplitude	-0.30	-0.44
y-axis amplitude	-0.46	-0.58
z-axis amplitude	0.70	0.86

TABLE Ⅱ
12 ATTRIBUTES OF ONE PERIOD OF THE PATIENT'S ELBOW HEAD MOTION

Attributes	Values of Sensor 1	Values of Sensor 2
Initial x-axis position	0.87	0.90
Initial y-axis position	-0.30	-0.32
Initial z-axis position	-0.62	-0.60
x-axis amplitude	-0.52	-0.85
y-axis amplitude	0.55	0.65
z-axis amplitude	0.64	0.80

C. Motion Recognition Model based on SVM

As described above, the patient was asked to repeat each motion 18 times, so total 36 sets of data were obtained. 24 of them were used in the training set and 12 used in the testing set. By using the LIBSVM software package developed by Chin-Jen Lin, it is easy to establish the motion recognition model.

However, in order to make the generalization performance of model better, there still have some factors need to be considered, such as the selection of the kernel type, the setting of the parameter value. Because the relation between the class labels and the attributes is nonlinear, so the RBF kernel is the reasonable choice. There are two parameters while using RBF kernel: penalty parameter C and kernel parameter γ. Here, the grid-search method was adopted to find the best C and γ.

IV. Results and Discussion

A. Experiments Results

The prediction results of SVM motion recognition model on the testing set are shown in Fig. 4, from which it can be seen that the recognition accuracy is 100%. The experiment results indicate that the established model based on SVM can recognize and classify the motion types such as elbow motion and elbow head motion perfectly.

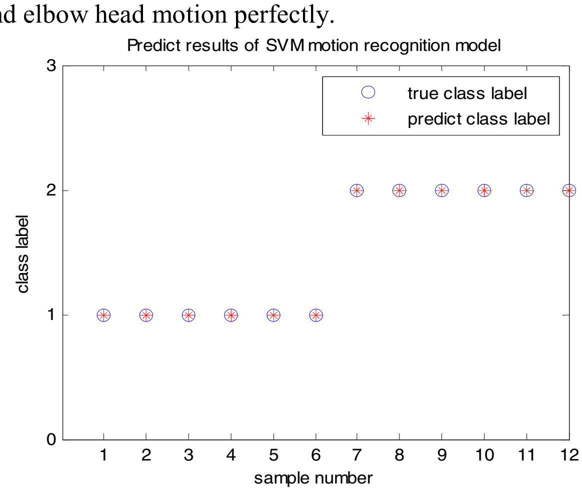

Fig. 4 Prediction results of SVM motion recognition model.

B. Discussion and the Future Work

From the above results, it can be concluded that based on the initial position and the amplitude of x, y and z axis, the two rehabilitation motions can be correctly recognized. However, these features cannot describe the real time status of rehabilitation motions, so it is necessary to find better feature extraction method to fully represent the status of the motion.

Additionally, our goal is to establish an online recognition model instead of traditional batch learning model like BP neural network, SVM, etc. So, one of our next task is to find some sequential learning algorithms.

V. Conclusion

In order to monitor the rehabilitation training of stroke patients in unsupervised situation, a wireless measurement system for upper limb motion recognition has been developed using tilt sensors, with motion recognition model based on SVM. The experiment results indicate that the hardware system and the proposed method can recognize the two typical and common rehabilitation motion types perfectly, which provides a well reference for further development of an fully automated and real-time system for stroke patient rehabilitation motion recognition.

Acknowledgment

Thanks given to Doctor Xudong Gu and Doctor Jianming Fu from The Rehabilitation Medical Center of The Second Hospital of Jiaxing, Zhejiang Province, China, for their great assistance during the data collection process. The clinical experiment involved human participants were approved by the Ethics Committee of The Second Hospital of Jiaxing.

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