SEMG and KNN Based Human Motion Intention Recognition for Active and Safe Neurorehabilitation

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Abstract

Accurate estimation of human motion intention is a hot topic in the area of rehabilitation robot. However, most of existing studies focus on the recognition accuracy, and pay little attention to the safety. In view of this situation, a safe method for human motion intention recognition is proposed, where K-Nearest Neighbor (KNN) algorithm is used to build the recognition model and the preprocessed sEMG signals are used as the inputs. Firstly, sEMG signals from seven muscles of human legs and angles of the hip, knee and ankle joints are recorded simultaneously during human walking, from which the training and test datasets can be built. The whole dataset was divided into ten time series subsets. Secondly, by comparing the distances between the test samples and the training samples, k nearest neighbors are selected and the associated joint angles can be estimated from calculation of the weight averages of the nearest neighbors. The estimations are filtered to obtain continuous and smooth angle trajectories. Due to that estimations can be maintained within the ranges of training data, the proposed method can ensure that the estimations are suitable and safe for patient rehabilitation. Finally, validation and comparison experiments were conducted to verify the method. Three key issues including the number of the nearest neighbors, the weight vector and the distance were considered for the design of a satisfied KNN sEMG-angle model. The root-mean-square errors for hip, knee and ankle joints are respectively 4.1°, 5°, and 3.5°.

1 Introduction

Presently, more and more people are losing their basic living abilities and their life quality is reduced by stroke, spinal cord injury(SCI) and other neuropathies. To solve those problems, researchers have developed various physical rehabilitation robotic systems which contribute to help the patients recover from the neural injury diseases [1–4]. The effect and efficiency of present rehabilitation systems are still needed to be improved. How to provide active training to the patients and how to improve their engagement are considered as key issues in neurorehabilitation [5]. To deal with these issues, many methods for human motion intention recognition based on sEMG signals are proposed [6–9]. However, few methods have been developed by consideration of the safety during rehabilitation training. SEMG signals can easily be lost and be affected by the variation of environment. In those cases, the recognition results will become inaccurate and patients can even be hurt, which is not fully researched in the literature. Therefore, an sEMG based method for accurate and safe recognition of human motion intention is proposed in this paper.

The sEMG signals have been extensively studied in the field of neurorehabilitation. To distinguish different motion patterns, many studies using sEMG signals have been carried out [10, 11]. However, less studies have been focused on estimation of continuous joint motion which is more suitable for rehabilitation robots [12]. Two kinds of methods are mainly used to estimate the continuous human motion intention by using sEMG signals. One method is to build forward dynamic neuromusculoskeletal models by using the Hill type models. Buchanan provided an overview of those methods that can be used to estimate muscle forces, joint moment and kinematics from neural signals [6, 7], however, it is a complex and physiological model containing too many parameters that cannot be directly measured. The other method is to build the relationships by machine learning methods, by which the sEMG-angle model can be built relatively easy, however, how to overcome deficiencies in overfitting and generalization should be further researched.

KNN algorithm is a non-parametric machine learning method. Different from other machine learning methods, it has no explicit modeling process. Actually, it's a representatively lazy learning method where the training samples are just saved during training and the distances between the training and test samples are calculated for recognition during test. Although the final regression model has relatively high computation complexity(since it accesses the entire reservoir of training data during testing), overfitting can be avoided [13]. KNN model can be designed without any prior knowledge and can describe the relationships between inputs and outputs just by selected data. Most KNN applications are focused on clustering or classification. Whereas, the algorithm can deal well with uncertain and nonlinear dynamic systems as well. For classification, the recognition result is the category, to which the most of nearest neighbors of the training dataset belong. For regression, the recognition result is the weight mean of nearest neighbors. Due to that lower limb joint angles and sEMG signals are periodic and repetitive during human walking, joint angles can be estimated based on the past data by KNN model. Moreover, the estimations can be maintained within suitable ranges, which are determined by the training samples. Therefore, the safety of estimations can be ensured, which is important for clinical application.

The remainder of this paper is organized as follows. Section II illustrates the proposed method. Data acquisition and processing are also given. The results and discussion are presented in Section III. This paper is summarized in Section IV.

2 METHOD

2.1 Experiment Platform

As shown in Fig.1, the lower limb rehabilitation robot(LLRR) developed at Institute of Automation, Chinese Academy of Sciences, is used as the experiment platform. It has two biomimetic legs. Hip, knee and ankle joints are designed for each leg. The LLRR can provide the patients with rehabilitation training in sitting and standing posture. When standing, patients can walk or run in assistance of the robot. The method proposed in this paper can be used to control this rehabilitation robot for the active and safe rehabilitation.

Figure 1: Lower limb rehabilitation robot developed at our institution.

2.2 Data Acquisition and Processing

Three healthy adults (all are males, 27 ± 3 years old) who are students in our institution took part in the experiment. All subjects are healthy and have no histories of leg or foot hurt in the pass three years. Research contents and purposes were consented by all subjects. In the experiment, the subjects were called to walk straight as naturally as possible. Four sessions of the experiment have been conducted for each subject.

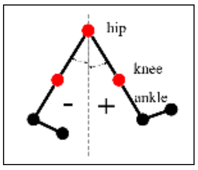
To simultaneously record joint angles and sEMG signals, a high-performing sEMG device (Delsys, Trigno) was used in the experiment. Signals from 16 channels can be recorded and each channel can be configured to connect with different sensors. Goniometer sensors (SG110 for ankle joint, SG150 for knee and hip joints) and sEMG sensors (IM for all muscles) used in this experiment are shown in fig.2. Considering the motion symmetry, only left lower limb joint sEMG signals and angles were recorded.

As generally defined, lower limb joint angles were recorded and analyzed in the sagittal plant, which is shown in Fig.3 [14]. The ends of goniometer sensors were parallelly and independently fixed on the left lower limb by special bandages, as is shown in Fig.4. Goniometer sensors were calibrated before each experiment.

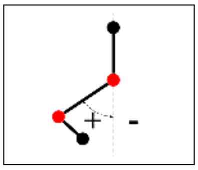
(a) sEMG sensor

(b) goniometer sensor

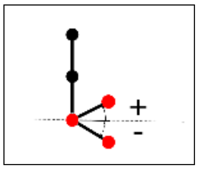
Figure 2: SEMG sensor and goniometer sensor.



(a) hip

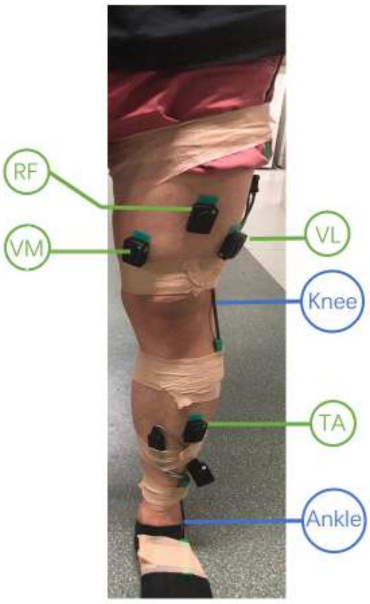


(b) knee

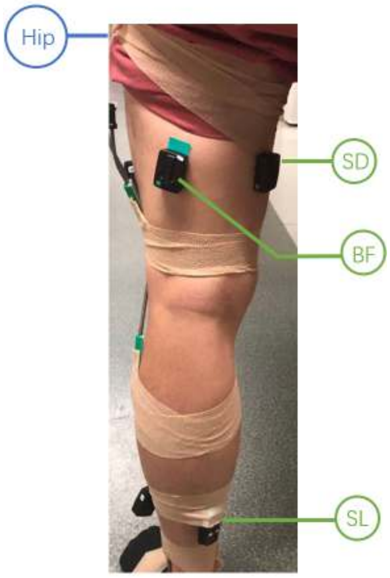


(c) ankle

Figure 3: Definition of lower limb joint angles.



(a) Front

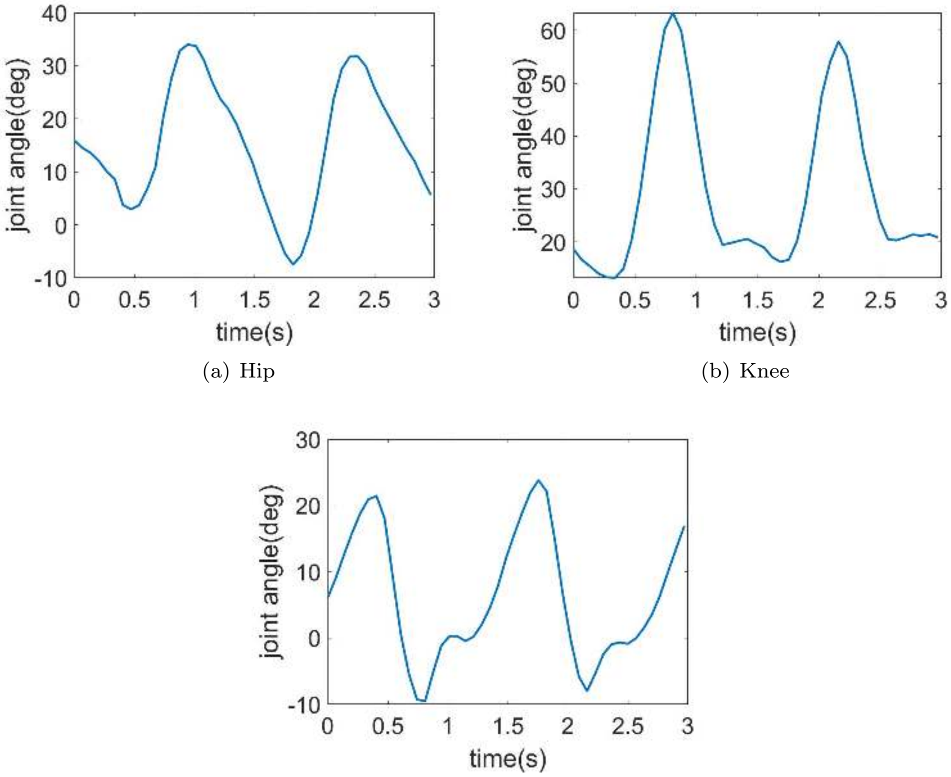


(b) Back

Figure 4: The positions to fix sEMG sensors and goniometer sensors. Smaller circles represent sEMG sensors. SEMG signals from five thigh muscles are used to estimate hip and knee joint angles. SEMG signals from two calf muscles are used to estimate ankle joint angle.

To make the data smooth, moving average (MOV) of the joint angles was computed with a sliding-time window, as follows:

$$\theta = \frac{1}{s}\sum_{i=1}^{s} f(i), \tag{1}$$



(a) Hip (b) Knee

(c) Ankle

Figure 5: Preprocessed joint angles from two walking periods.

where θ means the joint angle; $f(i)$ means the data within the window; and s means the data number. The window length was set to 15 and the sampling frequency of goniometer sensor was $150Hz$. That means the final data has ten data points in one second which is applicable for robot control. Fig.5 shows the preprocessed angle data.

SEMG signals from seven lower limb muscles, including rectus femoris(RF), vastus medialis(VM), vastus lateralis(VL), semitendinosus(SD), biceps femoris(BF), and tibialis anterior(TA), soleus(SL), were recorded. After shaving the hair and cleaning the skin, sEMG sensors were fixed on the muscle belly by special double-sided tapes, as is shown in Fig.4.

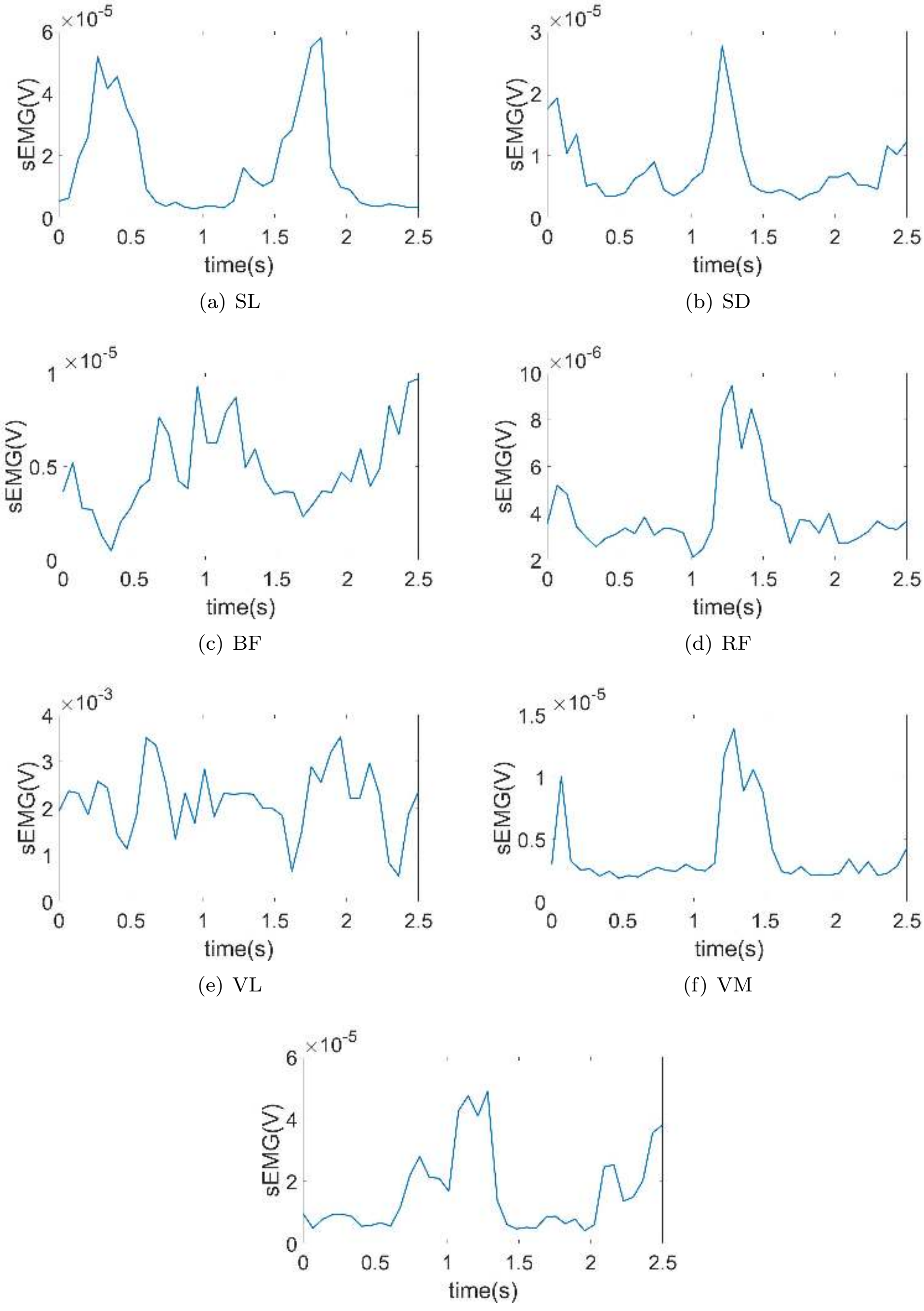
Raw sEMG signals are firstly high-pass filtered with a cutoff frequency of $20Hz$, then removed mean and finally low-pass filtered with a cutoff frequency of $400Hz$. To produce an enveloped sEMG signal which can represent the muscle activity, root-mean-square (RMS) value of sEMG data wasthe computed with a sliding-time window, as follows:

$$RMS = \sqrt{\frac{1}{s}\sum_{i=1}^{s} f^2(i)}. \tag{2}$$

Due to that the frequency of sEMG sensor is $1200Hz$, which is different with goniometer sensors', the window length was set to 120 to make the final data size same. Fig.6 shows the preprocessed sEMG data. The process is shown in Fig.7. Finally, the whole dataset is divided into ten subsets and each subset is related with time series.

2.3 KNN Based SEMG-Angle Modeling

Let $X \in R^{7\times n}$ and $Y \in R^{1\times n}$, X is the sEMG data of training dataset and Y is the angle vector, and X' and Y' are test data. The training samples can be ranked by the distances between X' and X. X_k is defined as kth neighbor of X.



(a) SL (b) SD

(c) BF (d) RF

(e) VL (f) VM

(g) TA

Figure 6: Preprocessed sEMG signals.

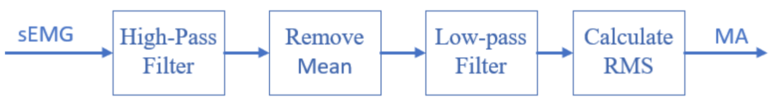


Figure 7: SEMG signal preprocessing, where MA represents muscle activity.

In this paper, the estimations can be expressed by:

$$\widetilde{\theta}_t = W \times [\theta_{1,t}\ \theta_{2,t}\ ...\ \theta_{k,t}]^T, \tag{3}$$

where $\widetilde{\theta}_t$ is the estimated joint angle at time t; $\theta_{k,t}$ is the kth nearest neighbor in the training data; W is a k -dimension weight coefficient column vector, which can be defined by:

$$W_k = \frac{exp(-(||X' - X_k||)^2)}{\sum_{i=1}^{k} exp(-(||X' - X_k||)^2)}, \tag{4}$$

where D is the distances between test and training data.

How to calculate the D is one of the key issues of the KNN algorithm. Two different distance equations, namely Eucliden distance(D_E) and Mahalanobis distance(D_M), are compared in this paper. D_E is given by:

$$D_E = \sqrt{(X' - X)^2}, \tag{5}$$

and D_M, taking into account the correlation of the data, is given by:

$$D_M = \sqrt{(X' - X)^T \Sigma^{-1} (X' - X)}, \tag{6}$$

where Σ is a covariance matrix of X.

The results of KNN algorithm are weighted and filtered to ensure that the estimations can directly be used on the LLRR. The algorithm flow chat is shown in Fig.8.

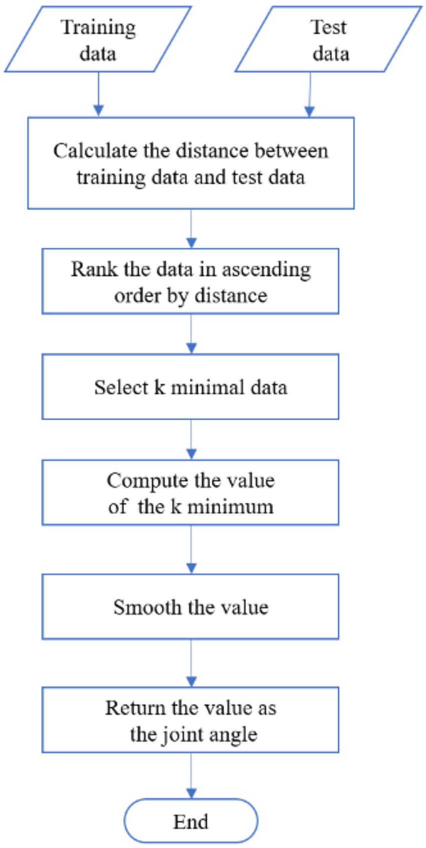


Figure 8: KNN algorithm flow chat.

3 Experiment and Discussion

Some experiments were conducted to verify the proposed method. Root-mean-square errors(RMSE) were calculated by the 10−fold cross validation method.

3.1 The Validation Experiment

Fig.9 shows the RMSE for the variation of k. Since the training data are cyclical and the nearest neighbors have no obvious difference, the variation of k has no enormous effect on RMSE. The nearest neighbors can be different with different distance equations, which can result in different regression results. Two distance equations mentioned in last section were compared. The RMSE for D_E and D_M are given in Table.1. It can be seen that the results of D_M are a little better than D_E', due to that different sEMG signals are relatively dependent.

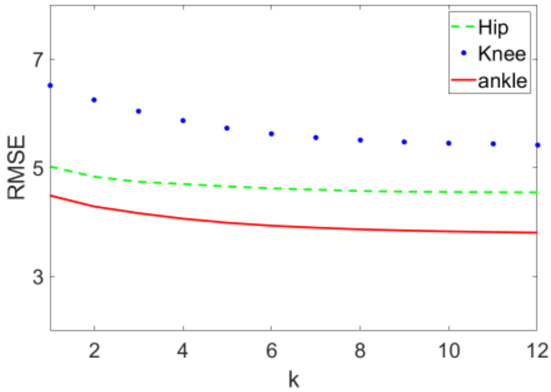


Figure 9: The RMSE for the variation of k

Table 1: The RMSE for D_E and D_M.

Distance	Hip	Knee	Ankle
D_M	4.34°	5.07°	4.31°
D_E	4.53°	5.24°	4.46°

In consideration of computation complexity and performance, D_E was selected as the distance equation, the k was selected to be 4 and the W was changed to $[0.4 \quad 0.3 \quad 0.2 \quad 0.1]$ to increase the weighting of neighbor points. Fig.10 shows the estimated and measured joint angles of one subject. It can be seen that, estimated trajectory can well fit the measured trajectory. The RMSE for hip, knee and ankle joints are respectively 4.1°, 5°, and 3.5°, as are given in Table.2.

Table 2: The RMSE for three subjects.

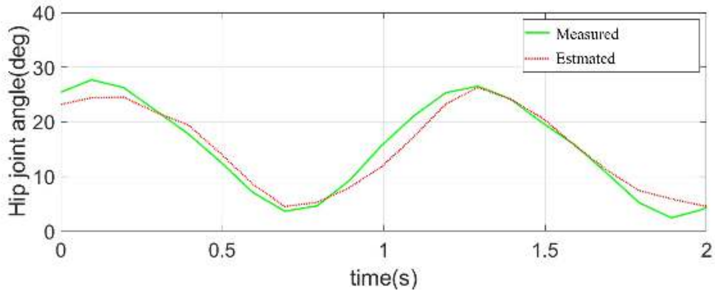
Subject	Hip	Knee	Ankle
1	4.06°	4.93°	3.69°
2	3.94°	5.14°	3.10°
3	4.17°	5.24°	3.73°

3.2 Comparison Experiments and Discussion

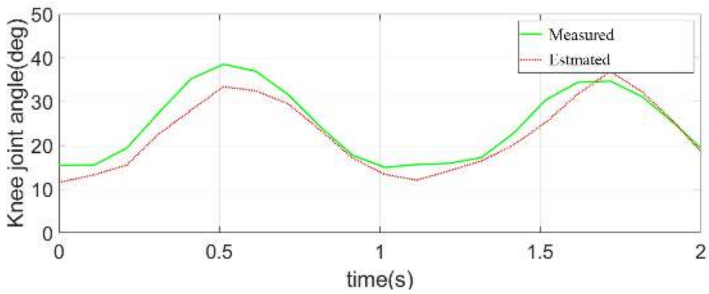
In the comparison experiment, a three-layer BPNN model was built to model the relationships between the sEMG signals and joint angles. The number of neurons in hidden layer was set to 20. The activation function of hidden layer is sigmoid transfer function and the loss of BPNN is RMSE. Gradient descent with momentum and adaptive learning rate backpropagation was used to train the neural network. After 3000 iterations and cross validation, the RMSE for BPNN model and KNN model are given in Table.3.

The sEMG sensors are easy to cause friction with human body and signals will be mixed with noises. To simulate this case, data from selected channels were mixed with gaussian noise. The results are given in Table.5.

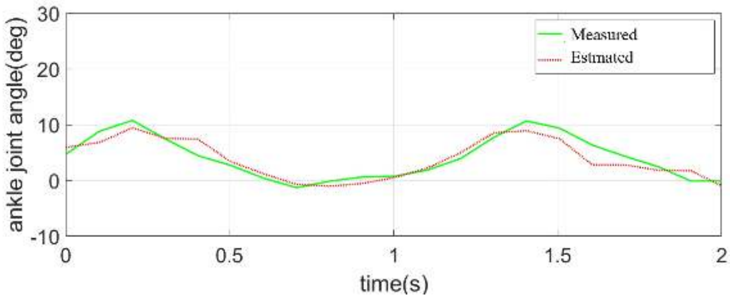
It can be seen from Table.4 and Table.5 that, KNN model can still have a good performance. On the contrary, BPNN model gave bad estimations. From Equation 3, final estimations of joint angles are weight averages of the nearest neighbors, which ensures that the estimation results can be maintained within suitable



(a) Hip



(b) Knee



(c) Ankle

Figure 10: The estimated and measured joint angles.

Table 3: The RMSE for BPNN and KNN.

Model	Hip	Knee	Ankle
BPNN	6.63°	9.18°	5.20°
KNN	4.04°	4.95°	3.25°

ranges. Therefore, it's safe for patient to do rehabilitation training, which however cannot be ensured by the black box model like neural networks when the test data are different from the training data.

4 Conclusions

A method for safe recognition of human motion intention is proposed, which is based on sEMG signals and KNN algorithm. The method can be used to build the relationships between sEMG signals and joint angles and the results can be maintained within suitable ranges. Three issues including number of neighbors, channel numbers of the lost signals, and the distance are discussed in this paper. Compared with BPNN, the designed KNN model can ensure robustness and safety. The method can be used on LLRR to achieve active and safe training for paralyzed patients. In the future, spinal cord injury and stroke patients will be tested to improve clinical feasibility.

Table 4: RMSE for signal missing. The first column represents channel numbers of signal missing.

number		Hip	Knee	Ankle
1	KNN	4.36°	6.93°	3.99°
	BPNN	4.04°	5.14°	11.47°
2	KNN	6.63°	9.18°	5.38°
	BPNN	10.63°	15.60°	20.30°

Table 5: RMSE for signal polluting. The first column represents channel numbers of signal polluting.

number		Hip	Knee	Ankle
1	KNN	4.21°	5.70°	4.01°
	BPNN	5.59°	7.97°	11.83°
2	KNN	6.72°	8.87°	5.78°
	BPNN	10.11°	14.98°	17.30°

5 Acknowledgments

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