Handle Reaction Vector Analysis with Fuzzy Clustering and Support Vector Machine during FES-Assisted Walking Rehabilitation

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Abstract. This paper proposed Fuzzy clustering of C means and K means methods to extract the lateral features of lower limbs movement from handle reaction vector (HRV)data. With C-means clustering, the SVM recognition rate of lateral features was usually above 90% while, with K-means clustering, the recognition rate was close to 85%. The best recognition rate was even reaching up to 97% for some individual subject. Then the samples from all subjects were processed together with the cross-validation. Our experimental results showed that the HRV signal could be used with fuzzy clustering and support vector machine to effectively classify the lateral features of lower limbs movement. It may provide a new choice for FES control signal. The optimizing of the algorism parameters can be introduced to get better control in the future.

1 Introduction

Paraplegic is impairment in motor and/or sensory function of the lower extremities. It is usually the result of spinal cord injury (SCI) [1] which affects the neural elements of the spinal canal. This means that paraplegic patients lose the voluntary control of neurological functions below the level of instinct. Inability to stand and walk, loss of sensation, bedsores, joint contractions, worsening of the cardiopulmonary function and loss of bladder and bowel control, etc. are the catastrophic impacts.

Rehabilitation is one of the methods to improve the life qualities of paraplegic patients. The most important aspect in the rehabilitation of paraplegic patients is to help them enhance or regain their lost functions, such as standing and walking [2]. To improve the gait and efficacy of paraplegic walking, functional electric stimulation (FES) is one of the good rehabilitation tools in helping paraplegic patients to regain their abilities to walk [3]. During FES-assisted paraplegic walking, a standard walker is used to help a patient to support his/her body and move forward by means of his/her upper limbs.

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C. Stephanidis (Ed.): Universal Access in HCI, Part IV, HCII 2011, LNCS 6768, pp. 489–498, 2011.

In the development of a FES system, one of FES key techniques is to choose its effective control signals. This paper proposed the force applied by the upper body of paraplegic patients to the walker, i.e. handle reaction vector (HRV), as a new FES control signal and tested its feasibility through the recognition of the lateral features of lower limbs movement from HRV signals during FES-assisted walking.

The force component of the vector in the x-,y-and z-axis can be respectively characterized the forward force, balance force and support force obtained by using walker. Among them, the definition of the coordinate system is set by the x-axis positive to the right of patients, the y-axis positive to the forward of patients,the z-axis positive to the upward of patients. Then the definition formula of HRV can be written as

$$[\mathrm{HRV}]=[\mathrm{HRV}_\mathrm{l},\mathrm{HRV}_\mathrm{r}]^\mathrm{T}=[F_{lx},F_{ly},F_{lz},F_{rx},F_{ry},F_{rz}]^T$$

To measure the HRV data during FES-assisted walking, a walker dynamometer system was developed with a 12-channel strain gauge bridge network as shown in Fig. 1.

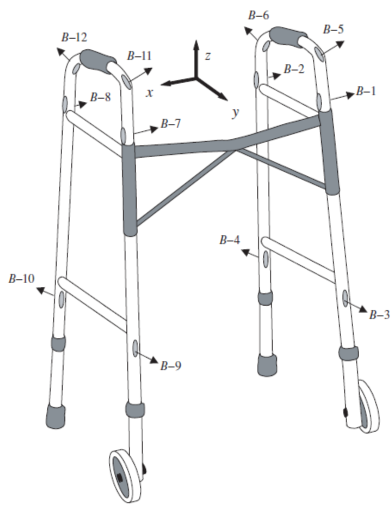

Fig. 1. Walker instrumentation with 12 strain gauge bridges [4]

Twelve strain gauge bridges, B-1 to B-12, were mounted on a standard walker frame to detect resultant forces in 3-dimensions. The forces were in lateral (X-axis), forward (Y-axis) and upward (Z-axis) directions.A full Wheatstone bridge was used with a bending pattern for the measurement of bending moments. The positions of the 12 strain gauge bridges were determined according to the bending moment distributions of the walker frame, and were calculated using the finite element analysis (FEA) method. The sensing data got by the twelve strain gauge bridges were amplified and filtered. Then they were transmitted by a cable to a PC for further analyzing and calculating the HRV.

2 Methods

2.1 Experiment and Data Collection

There were ten subjects, including 5 males and 5 females, involved in our experiment to collect the HRV data during FES-assisted walking. The subjects were required to follow a four-step training for walking until they were able to correctly complete a single continuous movement, then the formal test began. After the experiment, we obtained the upper three-dimensional force information of each subject. They were respectively marked as Flx, Frx, Fly, Fry, Flz, Frz. The figures 2-4 show the three-dimensional information of a subject.

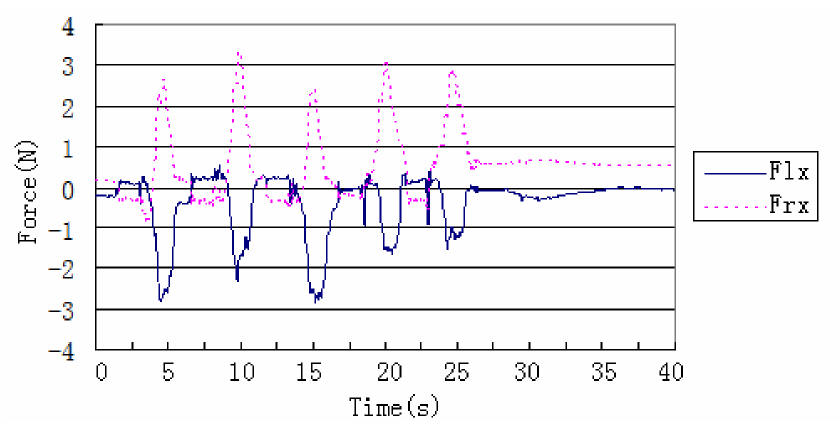

Fig. 2. Upper three-dimensional X direction force signal information

As shown in Fig.2,the X direction force which obtained by using walker characterized the forward force. In the experiment we got 5 standard gait cycles.The red line(Frx) was almost positive and the max amplitude was just more than 3 N. On the contrary,the blue one(Flx) was almost negative and the max amplitude was less than 3 N.

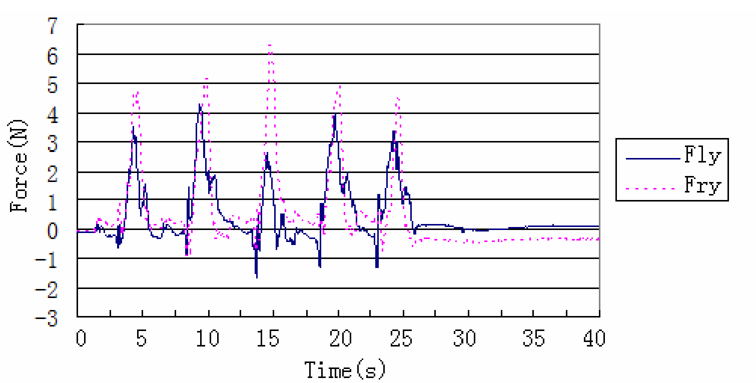

Fig. 3. Upper three-dimensional Ydirection force signal information

In Fig.3,the Y direction force characterized the balance force. In the 5 standard gait cycles,the red line(Fry) was almost positive and the max amplitude was a little more than 6 N. The blue one(Fly) was also positive and the max amplitude was a little more than 4 N.

In Fig. 4, the Z direction force characterized the support force. In the 5 standard gait cycles,the red line(Frz) was almost negative and the max amplitude was a little more than 20 N. The blue one(Flz) was also negative and the max amplitude was less than 20 N.

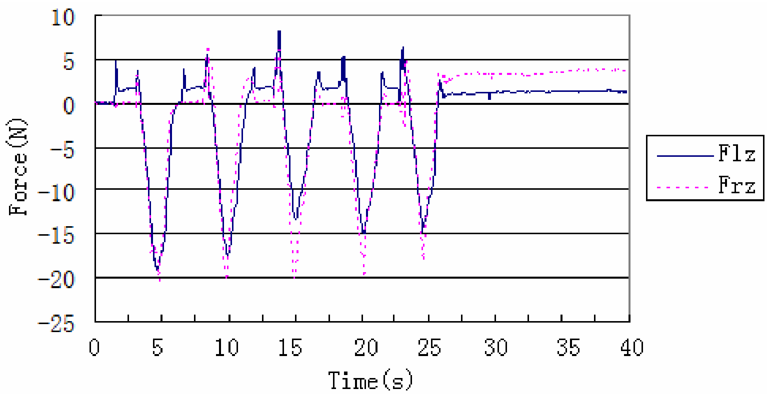

Fig. 4. Upper three-dimensional Z direction force signal information

2.2 Algorithm

Based on six-axis forces to explore walker signals reflecting different users situation of the lower extremities moving, we attempt to use a feature vector non-supervised learning method that is data clustering to evaluate the reliability of HRV measurement.

Fuzzy c-means Algorithm (FCM). Fuzzy c-means (FCM) [5-9]is a data clustering technique where in each data point belongs to a cluster to some degree that is specified by a membership grade. This technique was originally introduced by Jim Bezdek[10,11] as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters.

This iteration is based on minimizing our objective function that represents the distance from any individual event to our cluster center weighted by individual event's membership grade. The algorithm is an iterative optimization that minimizes the objective function defined as follow:

$$J_m = (u,v) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d^2(x_j, v_i) \tag{1}$$

With the following constraints:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j \tag{2}$$

Where $X = (x_1, x_2, \cdots x_j, \cdots x_n)$ is dimensional vector space for each force and n represents the number of feature vectors. u_{ij} is the membership of the j th data in the i th cluster c_i , m is a constant, the parameter m controls the fuzziness of the resulting partition. Using the Euclidean norm, the distance metric d measure the similarity between a feature vector x_j and a cluster centroid v_i in the feature space, i.e.:

$$d^2(x_j, v_i) = \left\| x_j - v_i \right\|^2 \tag{3}$$

The objective function is minimized when data points close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to data points far from the centroid. The membership functions and cluster centroids are updated by the following expressions:

$$u_{ij} = \{ \sum_{k=1}^{c} [\frac{d(x_j, v_i)}{d(x_j, v_k)}]^{2/m-1} \}^{-1} \tag{4}$$

And

$$v_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{5}$$

The FCM algorithm proceeds by iterating the two necessary conditions until a solution is reached. Each data point will be associated with a membership value for each class after FCM clustering. By assigning the data point to the class with the highest membership value, a segmentation of the data could be obtained. Concrete steps are as follows:

Step 1: Set the number of clusters c and the parameter m in (1). Initialize the fuzzy cluster centroid vector $V = [v_1, v_2, \cdots v_c]$ randomly and set ε.

Step 2: computer u_{ij} by (4).

Step 3: update v_i by(5).

Step 4: update u_{ij} by (4).

Repeat Steps 3 and 4 until the following termination criterion is satisfied:

$$\left| V_{new} - V_{old} \right| < \varepsilon$$

With fuzzy c-means feature extraction of the upper force information, there are two characteristic values of each dimension force in a gait cycle .They are respectively function value of each clustering center. Six groups forces are all together 12 eigenvalues.

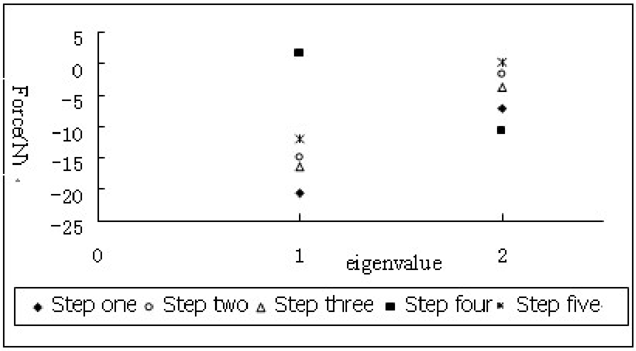

Fig. 5. FLz dimension force C - mean clustering results

As shown in Fig.5, the ordinate is the changes of FLz dimensional force in gait cycles.We can see that the right move is first in step two and the remaining are the left first.So the two eigenvalues obtained by C-means clustering are divisible.

Fuzzy k-Means Algorithm(FKM). The FKM algorithm [12] classifies each vector to all clusters with different values of membership between 0 and 1. This membership value indicates the association of a vector to each of the k clusters. Notice that the FKM algorithm does not classify fuzzy data, but crisp data into fuzzy clusters. We bring forward a modified subordination function u_{ij} [13], u_{ij} refers to the subordination degree of the ith sample to the jth category. We define a creterion function of clustering, that is

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} [u_{ij}]^{\beta} \left\| x_i - m_j \right\|^2 \tag{6}$$

and the constriction condition is

$$\sum_{i=1}^{k} \sum_{j=1}^{n} u_{ij} = c \tag{7}$$

For every vector V_i , i = 1,…n, its subordination function u_{ij} is compute as the following:

$$u_{ij} = \frac{(1/\left\| v_i - x_j \right\|^2)^{1/c-1}}{\sum_{i=1}^{k} (1/\left\| v_i - x_i \right\|^2)^{1/c-1}} \text{,j=1,2,…,k;c>1} \tag{8}$$

According to fussy theory, the FKM algorithm is described as following.
Input: clustering number K, parameter b and database with N objects.
Output: K clusters and with a minimum sum of the square of deviation.
S1: get clustering number K and clustering center according to tree structure.
S2: in the process of the kth iteration, use u_{ij} to update the clustering center c_i of each category,

$$c = \frac{\sum_{j=1}^{n} (u_{ij})^c x_j}{\sum_{j=1}^{n} (u_{ij})^c}, i = 1, \cdots, k \tag{9}$$

S3: for all the samples, the process will be finish if their subordination function won't change any more, if not, go back to S2.

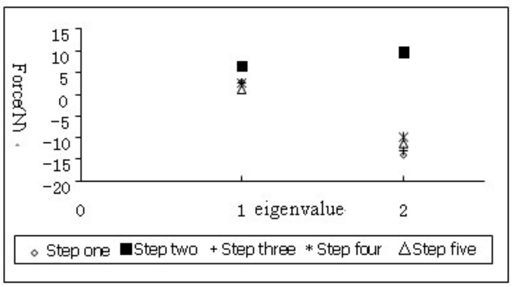

Fig. 6. FLz dimension force K- mean clustering results

This is k-means clustering results shown in Fig.6. We can get the same conclusion that the right move is first in step two and the remaining are the left first. So the two eigenvalues obtained by K-means clustering are also divisible.

Support vector machine (SVM). Support vector machine (SVM) have been developed by Vapnik (1995). SVM was developed to classify data points of linear separable data sets. The target result after finished training is separated into 2 groups which divided set by a separating hyperplane. The distance between the separated hyperplane and closest data points of dataset is called "the margin".SVM is gaining popularity due to many attractive features and promising empirical performance. It is based on Vapnik-Chervonenkis (VC) dimension of statistical learning theory and structural risk minimization principle.

SVM is evolved from the optimal separating line of a linear separable, and its basic idea is showed with a two-dimensional figure (see Fig.7). The square and hollow dot represents two types of samples, H for the classification line, H1 and H2 respectively represents the lines which are both nearest to and parallel to the classification line among the various types of categories in the sample line, the distance between them is called margin. The so-called optimal separating line is the lines which will not only be able to separate two groups (training error rate is 0) but also the largest classification margin.

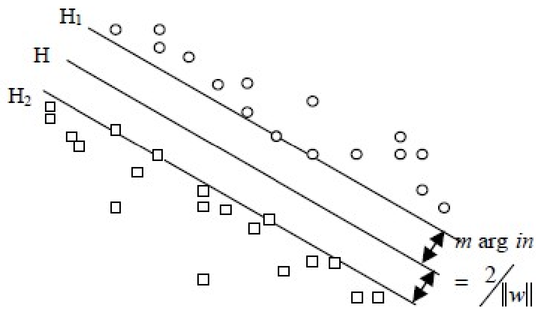

Fig. 7. Optimal separating hyperplane

3 Results and Discussion

Firstly, we tried to classify the lower extremity movement patterns of a single individual. With the C and K-means clustering in feature extraction, the recognition rate of SVM with RBF kernel functions is shown in Table1.

Table 1. Single individual RBF SVM recognition result

Clustering / the number	C	K
1	80.00	80.13
2	82.04	81.67
3	82.04	82.04
4	75.92	82.17
5	82.92	63.96
6	76.17	55.75
7	86.29	74.21
8	96.83	96.83
9	94.88	92.79
10	91.17	86.48
The average classification rate	84.83	79.55

The results of other nuclear functions are similar. So there is no need to list them separately. From the table we can see that for most subjects the recognition rate of lateral features is above 80.00%.With C-means clustering, the average recognition rate is close to 85.00% and the max recognition rate is up to 96.83 %. With K-means clustering, the average recognition rate is nearly 80.00% and the max recognition rate is close to 96.83%.It is highly separable.

Then the 50 samples from 10 subjects were processed together with the cross-validation The linear, RBF, polynomial and sigmoid kernel function were selected to test with SVM and the K-fold of Cross-validation values was chose as 2,3,4,5 separately in order to optimize SVM structure . The C and K-means clustering were used to extract feature firstly. The results are shown in Table 2 and 3. The recognition rate is the average of K-fold of Cross-validation values.

It can be seen from the two tables that when the data were expanded to all 10 subjects, the SVM recognition rate was decreased. With C-means clustering, the SVM recognition rate of lateral features was above 80.00% while, with K-means clustering, the SVM recognition of lateral features was just between 70.00% and 80.00%. There was a highest recognition rate of 85.50% with sigmoid kernel function and 4 fold cross-validation. In fact, the kernel function effect of SVM classifier is not very significant. The recognition rate with sigmoid kernel function was very slightly higher than the other kernel functions.

Table 2. The recognition results of SVM and C-means

kernel function / k	Linear	RBF	Polynomial	Sigmoid
2	78.85	75.50	81.25	84.31
3	82.11	72.96	80.02	78.06
4	83.95	83.81	78.53	85.51
5	79.92	78.55	73.56	83.66

Table 3. The recognition results of SVM and K-means

kernel function / k	Linear	RBF	Polynomial	Sigmoid
2	79.67	76.00	75.00	68.69
3	79.66	73.41	66.30	79.78
4	77.52	72.60	72.60	61.08
5	79.13	76.55	60.55	72.20

4 Conclusions

Our experimental results showed that the HRV signal could be used with fuzzy clustering and support vector machine to effectively classify the lateral features of lower limbs movement from HRV signals during FES-assisted walking. It may provide a new choice for FES control signal. In conclusion, this study provides a solid theoretical and experimental foundation for future work, such as the designing of more advanced functional electrical stimulation system in the future. The optimizing of the algorism parameters can be introduced to get better control in the future.

Acknowledgment. This research was partially supported by the National Natural Science Foundation of China (No.90920015, No.30970875, No.60501005), Joint Project of National Natural Science Foundation of China - Royal Society of Edinburgh of UK (No.30910494/C1009), The National High Technology Research & Development Program of China (No.2007AA04Z236), Biomedical Engineering Key Program (No.07ZCKFSF01300) and Intentional Cooperation Key Program (No.08ZCGHHZ00300) of Tianjin Science Technology Support Plan.

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