Motion Synthesis for Upper-Limb Rehabilitation Motion With Clustering-Based Machine Learning Method

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MOTION SYNTHESIS FOR UPPER-LIMB REHABILITATION MOTION WITH CLUSTERING-BASED MACHINE LEARNING METHOD

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ABSTRACT

Nowadays, mechanical devices such as robots are widely adopted for limb rehabilitation. Due to the variety of human body parameters, the rehabilitation motion for different patient usually has its individual pattern. Thus it is obviously not an optimal solution to use a single motion generator to suit all patients. Yet it would also be unpractical if we design a different motion or even a different mechanism for each user individually. Therefore, in this paper we seek to adopt clustering-based machine learning technique to find a limited number of motion patterns for upper-limb rehabilitation, so that they could represent the large amount of those from people who have various body parameters. Firstly, the trajectory of a specified rehabilitation motion are recorded from various subjects, and then 4 types of machine learning algorithms (spectral clustering, hierarchical clustering, self-organizing mapping neural network and Gaussian mixture model) are implemented and compared. It is shown that spectral clustering (SC) yields the best performance and is hereby adopted to generate three clusters of motion patterns. After regression of each cluster, three types of motion for upper limb-rehabilitation are constructed, which could reflect the trajectories' similarity and difference of people who have various body parameters. These work will provide help for the design of rehabilitation mechanisms.

Keywords: Rehabilitation mechanism; Machine learning; Clustering; Motion synthesis

1. INTRODUCTION

In recent years, mechanical assisting devices such as robots have been recognized as one of the most significant developments in emerging industries [1, 2]. The application of assisting machines in the field of rehabilitation not only provides effective training for the patients, but also reduces the burden on clinical staff and the cost of health care. As one of the most important rehabilitation devices, the upper limb rehabilitation

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mechanism is an automatic device for assisting patients with upper limb dysfunction to complete corresponding rehabilitation training and provide feedback information for rehabilitation physicians and patients. At present, the structural design of upper limb rehabilitation robots mainly includes end traction mechanism and exoskeleton mechanism [3]. The former basically takes linkages or serial robot as the main mechanism, and realizes the repeated rehabilitation training by supporting and pulling the end of the patient's upper limb. For example, Raymond Holt designed a dual-arm robot called iPAM [4] and a 2-DOF upper limb rehabilitation robot named UECM was developed by Zhang [5]. The exoskeletons, on the other hand, usually have a kinematic mechanism consistent with the human body, a wearable mechanism that is designed to contact the patient's limb and the exoskeleton structure, and transmit forces to the limb for realizing the auxiliary rehabilitation training. Examples of this type of rehabilitation mechanisms include the 7-DOF exoskeleton powered arm CADEN-7, which was designed by Perry et al. [6], and a 3-DOF EMUL rehabilitation robot that was developed by Haraguchi from Osaka University [7]. Considering the cost of these multi-DOF rehab devices is usually quite expensive, designers also proposed a series of one-DOF rehab mechanisms for specified tasks. Naghavi [8] proposed an active one-DoF mechanism for knee rehabilitation. Franci [9] designed a parallel mechanism for modelling passive motion at the human tibiotalar joint. Our group [10] also proposed a cam-linkage mechanism for lower-limb rehabilitation with Kinematic-Mapping based motion synthesis approach.

Since human body parameters vary among each individual, apparently the suitable rehabilitation motion for different patients should also have different patterns. If one-DOF rehabilitation mechanisms are adopted for its simpler structure and lower cost, then a group of different mechanisms need to be prepared to adjust different users since one-DOF mechanisms can only generate one specified motion. On the other hand, to address such issues, most of the current multi-DOF limb rehabilitation mechanisms are controlled and programed to produce training trajectories in different scales to reflect the limb length. Yet, body parameters such as height and weight also affects the trajectories but they are usually not considered. It would also be unpractical to customize a different motion or mechanism for each user individually. Therefore, in this paper, we use clustering technique to find a limited number of motion patterns for upper-limb rehabilitation, so that they could represent the large amount of those from people who have various body parameters.

Cluster analysis technique is an important tool in the fields of machine learning, data mining and pattern recognition, etc. It classifies similar objects into the same class and separates objects with large distinction into different classes according to the relevant characteristics of data objects, and potential intrinsic links are found to support decision making [11, 12]. A series of clustering algorithms have been proposed in recent years, e.g. spectral clustering (SC) [13], hierarchical clustering (HC) [14], self-organizing mapping neural network (SOM) [15] and Gaussian mixture model (GMM) [16]. These clustering technique has broad application field and prospects due to its versatility, applicability and feasibility, such as MCI patient detection, image processing, human motion analysis and dynamic data processing [17-19].

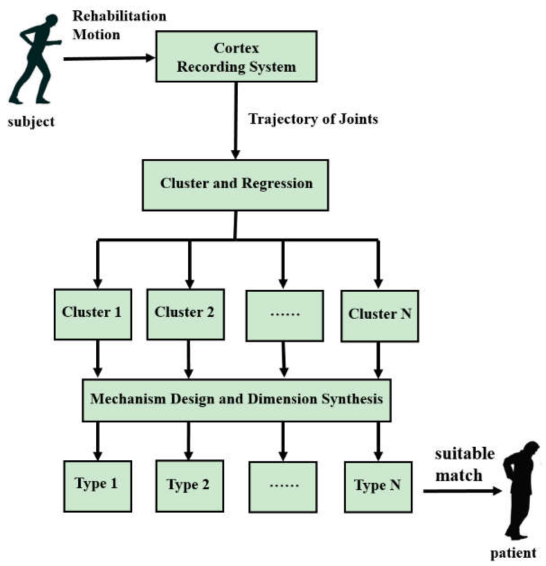


Fig.1 Design procedure of upper limb rehabilitation robot

This paper proposes a method to find a limited number of suitable motion generator for upper limb rehabilitation of patients with various body parameters. As shown in Fig.1, firstly, a number of healthy subjects are invited into the data collecting process. The height of the subjects vary from 158cm~187cm, the weight range from 42kg~97kg and the arm length from 45cm~60cm. We take the movement of the upper-limb during a boating motion as the rehabilitation training motion. The subjects' upper-limb motion trajectory and their respective physical parameters are acquired by Cortex Version 5.0, a high-precision labeled motion capture system. Then, 4 types of machine learning algorithms (spectral clustering, hierarchical clustering, self-organizing neural network and Gaussian mixture model) are implemented and compared in Section 3, and three clusters are established. After regression of each cluster, three types of motion for upper limb-rehabilitation are constructed. We will complete two mechanism design examples using one cluster of the rehabilitation motion, including a spatial multi-DOF mechanism with an accurate realization of the task, and a planar one-DOF mechanism that could approximately lead through the task rehabilitation motion.

2. ACQUISITION OF UPPER-LIMB REHABILITATION TRAJECTORY DATA

Our data acquisition environment is as follows: The computer's operating system is a 64-bit Windows 10 operating system, the processor is Intel (R) Core (TM) i5-7600 CPU @ 3.50GHz, RAM 8.00GB, and a high-precision labeled motion capture system named Cortex (the right one of Fig.2) is used to record data and trajectory extraction. A total number of 47 healthy subjects have participated in the data collecting process, who wear the experiment equipment for the motion capture (the left one of Fig.2).

Fig.2 Subject wearing the motion capture device (left) and the motion recording equipment Cortex (right)

8 cameras as showed in Fig.2 are used to record the real-time trajectory of 25 small balls fixed to each joint of the subject and to acquire the motion trajectory of each body part of the subject. And the spatial location information of the specified 3 points (S, E and W) on the left arm and 3 points on the foot and waist in a motion cycle are fixed, where the three points S, E and W represent respectively three small balls fixed to the shoulder joint, the elbow joint and the wrist joint. Fig.3 shows the schematic diagram of the trajectory acquisition environment and the location division of the 8 cameras.

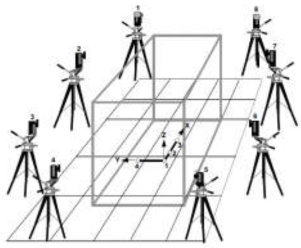


Fig.3 The environment of trajectory acquisition

Then, after learning from the demonstration video of rehabilitation training motion, the subjects accomplished the specified boating movement (Fig.4) for upper limb rehabilitation training in the environment of trajectory acquisition. Debugging and coordinate calibration of the experiment equipment were also completed before operating the device to record the trajectory data.

Fig.4 The demonstration of upper limb rehabilitation motion

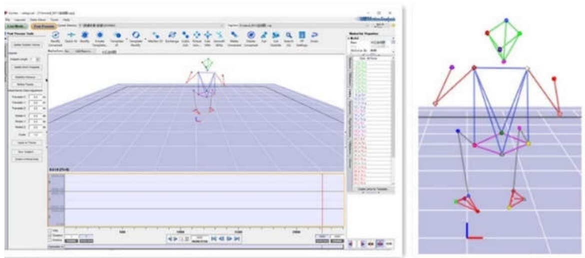


Fig.5 Cortex Operation interface and distribution diagram of the 25 points which were fixed on each joint

Fig.5 illustrates a distribution diagram of the 25 points which are fixed on each joint of the subject's body. In order to obtain the relative spatial coordinate locations of the joint points of the upper limb rehabilitation motion, the left arm joints S (shoulder), E (elbow) and W (wrist) of the subject are extracted. And 3 moving points in the human foot and waist are also extracted for relative conversion of the world coordinate and the moving reference during the following data preprocessing.

3. CLUSTERING OF THE REHABILITATION MOTION DATA

After capturing the raw data from the subjects, in this section, the data sets are firstly pre-interpolated and processed to reduce the noises. Then, since the coordinates are measured in the fixed reference, we need to eliminate the effect of moving references so that the data is not impacted by the location and direction of the subjects. The three points on the subject's foot and waist are used to establish the reference frame that follows each subject, and the coordinates of 3 points (S, E and W) on the upper limb are transformed into the representation in the reference frame. Suppose the world frame is {A} and the reference frame is {B}, then the homogeneous transformation matrix can be expressed as follows:

$$H_B^A = Rot(Z,\eta)Rot(Y,\delta)Rot(X,\varepsilon)Trs \tag{1}$$

$$H_B^A = \begin{bmatrix} R & d \\ 0 & 1 \end{bmatrix}, R \in SO(3) \tag{2}$$

$$d = [dx, dy, dz]^T \tag{3}$$

R represent the first 3 rows and 3 columns of the rotation matrix, which could be constructed as follow:

$$R = \begin{bmatrix} X_B X_A^T & Y_B X_A^T & Z_B X_A^T \\ X_B Y_A^T & Y_B Y_A^T & Z_B Y_A^T \\ X_B Z_A^T & Y_B Z_A^T & Z_B Z_A^T \end{bmatrix} \tag{4}$$

where $X_A = [1\ 0\ 0], Y_A = [0\ 1\ 0], Z_A = [0\ 0\ 1]$, and X_B,Y_B,Z_B are the unit vector of X, Y and Z axis of {B} frame in {A}, respectively.

Therefore, the location vector's transformation relationship of any point P between the coordinate {A} and the coordinate {B} could be obtained as follow:

$$P^A = H_B^A P^B, P^B = (H_B^A)^{-1} P^A \tag{5}$$

Through the above coordinate transformation, the coordinate of the upper limbs S, E and W in the reference frame of each subject's torso are obtained. Therefore, the possible errors caused by location and direction of subjects in the world coordinate could be eliminated before the subsequent clustering and regression.

3.1 Expansion of the database

To improve the performance of clustering, it is a commonly adopted strategy to expand the database by separating one original set of data to multiple sets [20]. In our case, to expand the database, we uniformly sample 24 frames in a complete motion of about 120 frames. Thus, the database is now expanded to 94 sets, wherein each sample data was 24×19 dimensions. The increase of number of frames also helps to reduce the computational cost of the algorithm.

In order to further reduce the computational cost in the clustering process, the inverse kinematics equation is adopted. Instead of using the captured joint coordinate parameters directly to reflect the trend and pattern of the motion, we convert these information into the expression of angles between the upper limb and the torso.

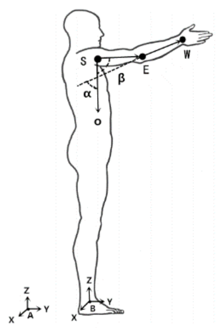


Fig.6 Main angle and coordinate setting of upper limb motion

Fig.6 shows that the angle α and angle β, which represent the angle between forearm, arm and torso, where $\mathbf{SO} = [0,0,-1]$ represents the torso vector.

$$\alpha = \arccos \frac{\mathbf{SE} \cdot \mathbf{SO}}{\|\mathbf{SE}\| \|\mathbf{SO}\|} \tag{6}$$

$$\beta = \arccos \frac{\mathbf{EW} \cdot \mathbf{SO}}{\|\mathbf{EW}\| \|\mathbf{SO}\|} \tag{7}$$

Let us define a new variables:$\theta = \alpha + \beta i$ to reflect the trend and pattern of the upper limb poses during the boating rehabilitation motion. Thus the computational complexity of the algorithm is now reduced from O

(94×120×19) to O (94×24×2) after the conversion from point coordinate to angle. It greatly reduces the storage capacity requirements of the training process during clustering algorithm, and could hereby improve the efficiency.

3.2 Clustering of the motion and evaluation of the results

Before the clustering of the 94 sets of motion data, it is necessary to determine the number of clusters. In this paper, we consider the characteristics of the boating motion data, and first obtain the optimal number of clusters based on k-means algorithm. The optimal cluster number is then obtained for spectral clustering (SC), hierarchical clustering (HC), self-organizing neural network (SOM) and Gaussian mixture model (GMM). Different numbers of clusters are set and substituted into the algorithm, and the performance of clustering quality could be compared based on the IASC（Improved Average Silhouette Coefficient）:

$$\mathrm{IASC} = \frac{1}{n}\sum_{i=1}^{c}\sum_{k=1}^{n_i}\frac{b(k)-a(k)}{\max\{a(k), b(k)\}} \tag{8}$$

where n is the total number of samples, c is the cluster number, n_i is the number of samples in the i-th cluster. The a(k) is the distance between the k-th sample and its cluster's centroid, and b(k) is the minimum distance between the sample and centroid the other c-1 clusters. Although the improved average silhouette coefficient has the same expression as the traditional silhouette coefficient, a(k) and b(k) do not require the repeated calculation of the distance between samples. From the IASC result shown in Fig.7, it could be seen that the optimal cluster number is 3.

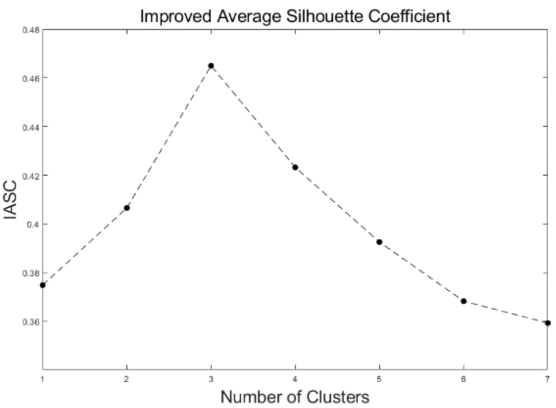


Fig.7 The IASC of different number of clusters based on k-means clustering algorithm

Next, the aforementioned 4 algorithms are implemented. Fig.8 presents the clustering results of them, and figure 9 shows their similarity matrix. From the regression results in the right ones of Fig.8, it could be noticed that starting point and ending point are not closed, which is because generally the subjects do not end exactly the same as the start. Through visual comparison of Fig.8 and Fig.9, we could observe that the SC and HC yields better clusters than SOM and GMM. To present a numerical analysis for the validity of these algorithms, the properties of the results are further investigated.

In general, there are three approaches to investigate cluster validity. (1)External criteria, which means that the results of a clustering algorithm is evaluated based on a pre-specified structure imposed on a data set and reflects users' intuition about the clustering structure of the data set. (2)Internal criteria, which indicates that we use the inherent features and magnitudes of the dataset to evaluate the clustering validity of a clustering algorithm, while the structure of the dataset and the pre-classification label are unknown. (3)Relative criteria, where a clustering structure is evaluated by comparing it with other clustering schemes by setting different parameters, and finally selecting the optimal parameter setting and clustering mode [21,22].

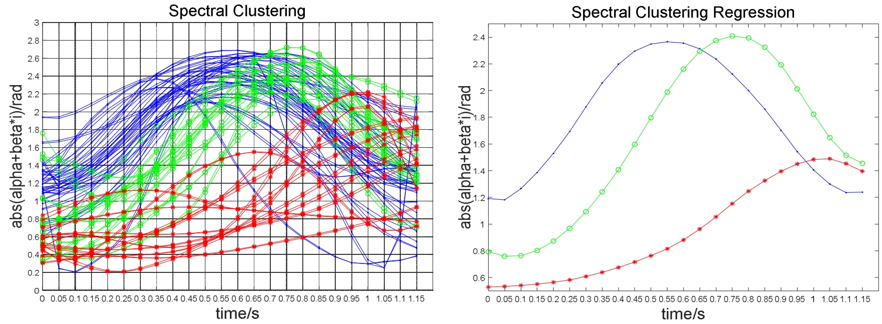
In this paper, the above 4 algorithms are sequentially evaluated by using internal criteria method, which is usually defined by cluster compactness and separation.

Compactness: It indicates the average scattering within c clusters based on variance. A smaller value of this term is an indication of a better compact cluster. The definition is obtained as follows:

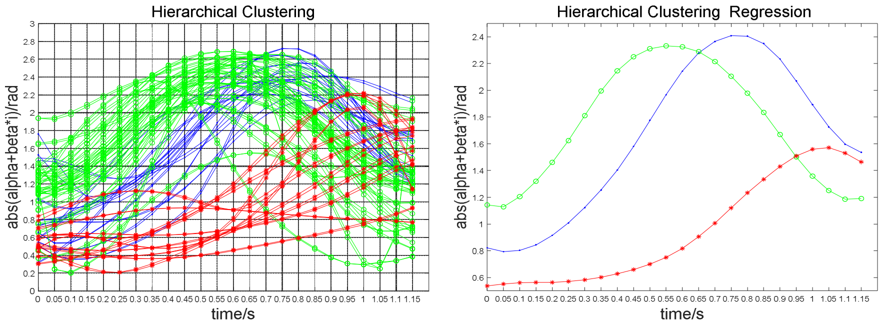
$$\sigma_\theta = \frac{1}{n}\sum_{k=1}^{n}(\theta_k - \bar{\theta})^2 \tag{9}$$

$$\sigma_{v_i} = \sum_{k=1}^{n_i}(\theta_k - v_i)^2/n_i \tag{10}$$

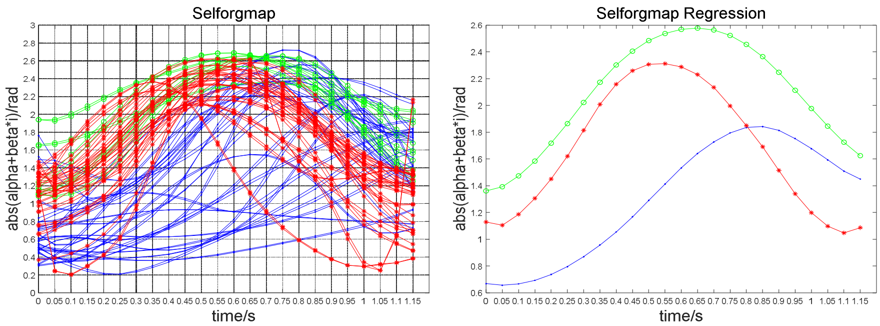
where $\theta_k = \mathrm{abs}(\alpha + \beta i), n = 94, \bar{\theta} = 1/n\sum_{k=1}^{n}\theta_k$, v_i and n_i are respectively the center and the samples' number of i-th cluster. So the $\mathrm{Scat}(c)$ presents the average dispersion of all clusters.



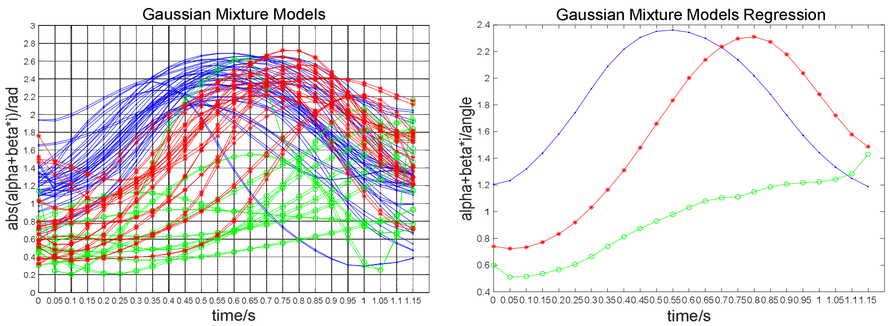
(a) SC



(b) HC



(c) SOM



(d) GMM

Fig.8 The comparison of 4 clustering algorithms (left) as well as the regression of each clustering result (right)

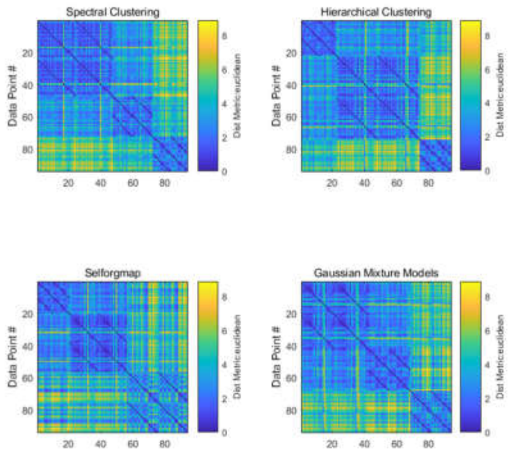


Fig.9 The similarity matrix of 4 cluster algorithms

$$\mathrm{Scat(c)} = \frac{1}{c}\sum_{i=1}^{c} \|\sigma_{\theta}\| / \|\delta_{v_i}\| \tag{11}$$

where c is the number of clusters set in advance.

Separation: It indicates the total separation between the c clusters such as an indication of inter-cluster distance. The goal is that the density among clusters should be lower in comparison with the density in the considered clusters. The definition is obtained as follows:

$$\mathrm{Dis(c)} = \frac{D_{max}}{D_{min}}\sum_{k=1}^{c}\left(\sum_{z=1}^{c}\|v_k - v_z\|\right)^{-1} \tag{12}$$

where D_{max}=max($\|v_i - v_j\|$) and D_{min}=min($\|v_i - v_j\|$) are respectively the maximum distance and minimum distance between any two clusters ($\forall$i,j$\in${1,2,…c}).

When Sat(c) and Dis(c) are not in the same order, k as a weighting factor can balance the influence to SD(c) as follows:

$$\mathrm{SD(c)} = \mathrm{Scat(c)} + k\mathrm{Dis(c)} \tag{13}$$

The smaller $\mathrm{Scat(c)}$ indicates better compactness and the greater similarity of the upper limb rehabilitation trajectories in the same cluster. The smaller $\mathrm{Dis(c)}$ indicates better separation and greater difference of the upper limb rehabilitation trajectories which belong to different clusters.

Table1 Clustering validity of different algorithms

Clustering algorithm	Scat(c)	Dis(c)	SD(c)
SC	0.3570	0.4548	0.8118
HC	0.3563	0.5052	0.8615
SOM	0.3747	0.5277	0.9024
GMM	0.5505	0.4053	0.9558

Table1 shows the SD(c) of the 4 clustering algorithms. From the table it could be seen that spectral clustering algorithm's SD(c) is the smallest, and it mostly have a better performance in compactness and separation compared with other algorithms. Therefore, considering the clustering quality, spectral clustering algorithm is adopted in our approach to cluster the upper limb rehabilitation trajectory data sets.

The idea of spectral clustering algorithm comes from the theory of spectral partitioning. It constructs undirected weight maps based on eigenvalues between samples, and maps high-dimensional spatial data to low-dimensional, which has unique advantages for processing non-convex data sets. Suppose each data sample is regarded as the point V in the graph, and the edge E between the points is weighted by the weight W according to the similarity between the samples, so that an undirected weighted graph G = (V, E) is obtained based on the sample similarity. Then the clustering problem can be transformed into the graph partitioning problem on graph G.

Adopting the spectral clustering method, we could describe the algorithm in this paper for the clustering of upper-limb rehabilitation data as follows:

Input: data set $\theta = \{\theta_1, \theta_2, \dots, \theta_k, \dots, \theta_{94}\}$ and scale parameter σ=9.

Output: cluster division $C\ (c_1, c_2, \dots, c_i, \dots, c_n)$.

a) Obtain the best cluster number c (c=3) from the clustering cluster adaptive algorithm.

b) The similarity matrix A is constructed by a fully connected Gaussian kernel function, where $A_{ij} = \exp(-1/2\sigma^2\|\theta_i - \theta_j\|^2), \forall i, j \in \{1,2, \dots 94\}$, if $i = j$, $A_{ij} = 0$;

c) The sum of the elements of the i-th row of the similar matrix A is taken as the main diagonal element of the i-th row of the matrix D, and the matrix D is named the metric matrix, and the Laplacian matrix is constructed by it: $L = D^{-1/2}AD^{1/2}$.

d) The 3 eigenvectors corresponding to 3 largest eigenvalues are obtained by solving matrix L, and construct the matrix $X = [x_1, x_3, x_3]$ with 3 eigenvectors.

e) Normalize the row vector of matrix X to Y, where $Y_{ij} = X_{ij} / \ (\sum X_{ij}{}^2)$.

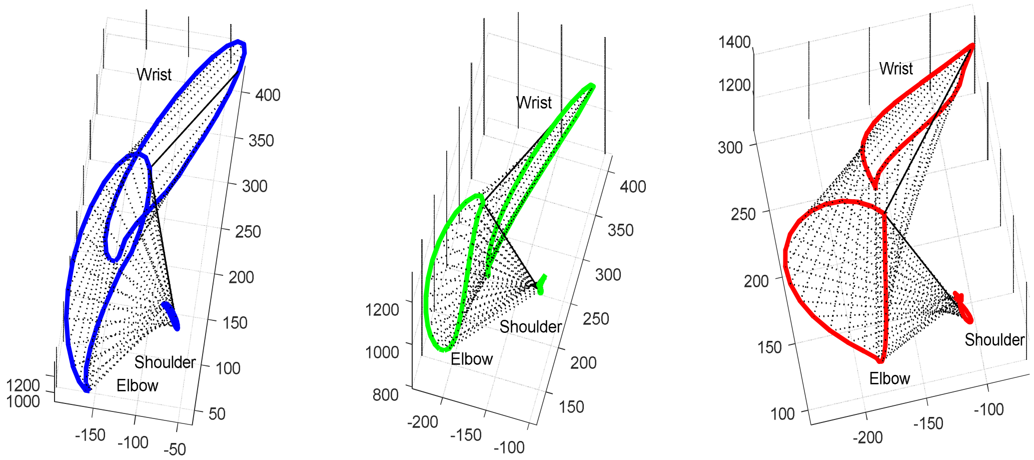


Fig.10 Upper limb rehabilitation joint trajectory in Fig.8 (a): Blue cluster (left), Green cluster (middle) and Red cluster (right)

f) Each row of the matrix Y is regarded as a sample of the space R_3. The sample dimension is 94×3 and the eigenvectors are clustered by the k-means algorithm.

g) The sample point θ_k is divided into the c_i cluster when the k-th line of the matrix Y is divided into the c_i cluster. It also indicates that the k-th subject's upper limb rehabilitation motion trajectory is classified into the c_i cluster.

In Fig.8 (a), we have already shown the cluster result of the spectral clustering algorithm for the data set θ. To actually obtain the pattern and trend for each cluster of rehabilitation motion, we still take the 3 points' (shoulder joints S, elbow joints E and wrist joints W) spatial coordinates of each cluster generated by spectral clustering algorithm, and conduct a regression for each cluster of motion. Fig.10 shows the regression result of the S, E, W joints' spatial trajectory of the three type of clusters in Fig.8 (a). It could be noticed that the shoulder joint trajectory is a small closed curve in all types of motion, which is generally treated as a fixed sphere joint in practical design cases.

4. CONCLUSION

This paper adopts clustering-based machine learning method to find a limited number of motion patterns for upper-limb rehabilitation, so that they could represent the large amount of motion of people who have various body parameters. After acquisition of 94 groups of rehabilitation motion data, 4 types of machine learning algorithms are implemented and compared. It is shown that spectral clustering algorithm yields the best performance and is hereby adopted to generate three clusters of motion patterns. After regression of each cluster, three types of motion for upper limb-rehabilitation are constructed, and future work will include the design of associated rehabilitation mechanisms and the establishment of the institutional supervised learning model based on physical parameters which have be recorded.

ACKNOWLEDGEMENT

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Appendix: Coordinates for the elbow and wrist trajectories of the blue cluster

Index	Elbow	Wrist
1	[-160.12, 44.009, 1071.1]	[-148.86, 190.19, 947.29]
2	[-154.27, 34.923, 1083.0]	[-154.48, 187.71, 982.99]
3	[-158.70, 33.887, 1092.9]	[-159.57, 191.31, 1027.6]
4	[-167.56, 41.237, 1102.1]	[-162.12, 201.02, 1075.3]
5	[-177.38, 55.813, 1111.5]	[-161.14, 217.13, 1125.2]
6	[-186.44, 77.343, 1122.1]	[-155.93, 238.71, 1172.4]
7	[-192.85, 104.09, 1133.8]	[-146.87, 263.78, 1212.8]
8	[-195.66, 133.45, 1145.7]	[-133.93, 292.37, 1246.3]
9	[-194.73, 165.34, 1157.7]	[-118.18, 322.1, 1269.6]
10	[-190.04, 197.0, 1168.7]	[-101.28, 350.31, 1280.9]
11	[-182.37, 225.69, 1177.2]	[-83.503, 376.95, 1280.3]
12	[-172.08, 251.43, 1182.7]	[-66.698, 399.41, 1266.8]
13	[-160.38, 271.69, 1184.2]	[-52.604, 415.75, 1241.9]
14	[-148.74, 284.86, 1180.8]	[-41.495, 425.82, 1205.2]
15	[-137.57, 290.93, 1172.2]	[-34.809, 428.18, 1159.1]
16	[-128.33, 288.92, 1158.2]	[-33.158, 422.74, 1108.0]
17	[-122.07, 279.37, 1139.9]	[-36.564, 409.53, 1052.2]
18	[-119.04, 262.54, 1117.4]	[-44.822, 389.52, 997.6]
19	[-119.80, 240.16, 1092.9]	[-56.543, 365.28, 950.83]
20	[-124.09, 215.41, 1069.8]	[-70.726, 338.04, 915.08]
21	[-124.09, 215.41, 1069.8]	[-70.726, 338.04, 915.08]
22	[-130.33, 193.41, 1051.5]	[-81.442, 318.04, 902.71]
23	[-139.97, 171.41, 1046.6]	[-91.574, 298.04, 887.25]
24	[-146.64, 149.41, 1046.7]	[-103.31, 278.04, 887.62]
25	[-152.75, 127.41, 1047.4]	[-117.50, 258.04, 895.18]
26	[-157.81, 105.41, 1048.8]	[-131.20, 238.04, 905.75]
27	[-161.26, 83.409, 1050.9]	[-141.38, 218.04, 916.53]
28	[-162.55, 61.409, 1054.0]	[-145.47, 198.04, 925.02]