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A Fuzzy C Means Clustering Approach for Gesture Recognition in Healthcare

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Abstract: The aim of this novel work is to recognize 12 health care linked gestures from young individuals of 20-40 years of age group. Due to constant sitting in a specific posture for deskbound jobs, functioning of joints and muscles of persons are deteriorated. The scope of this work is to recognize the early stage symptoms of those physical disorders and notify the persons about their decaying health. This medical knowledge based system also prescribes an exercise based on recognized disorder after consulting doctors. The work deals with principal component analysis for linear dimensionality reduction and recognition using fuzzy c means algorithm. The overlapping of gestures in feature space demonstrates the fuzziness of the input. This easy but effective technique provides a high accuracy of 96.0201% in 0.0439 second. The results are compared with those obtained from other standard clustering methods using McNemar's Test, thereby validating the proposed method.

Keywords: Fuzzy C means, gesture recognition, Kinect sensor, healthcare, principal component analysis.

Introduction

The working nature of young individuals is changed widely now-a-days. Most of the office works are based on computers thus the employees need to spend about eight to nine hours continuously in sitting postures. The tendency to do physical exercise among these individuals is fading away. Thus several physical disorders related issues are causing major threats to young persons. The gestures recognized in this paper are the early-stage symptoms shown by young individuals due to fatigue or overstrained joints and muscles. The proposed scheme is widely applicable for places like multi-national companies where not only the health of the employees is hampered but also due to this uneasiness of doing jobs, the productivity of the company deteriorates. The purpose of this paper is to recognize the disorders like prolapse intervertebral disc, lumbosacral strain, spasmodic torticollis etc.In this work, 12 gestures related to healthcare is recognized using Microsoft's Kinect sensor [1]. Kinect sensor can detect skeleton of an employee while working in his/her office premises using 20 body joint co-ordinates [2]. The Kinect sensor detects the 3D image representation of a person facing the sensor [3]. It tracks the skeleton of the person standing/sitting in front of it within a finite range of 1.2 to 3.5 m distance using a set of visible and IR cameras [4, 5, 6].

Gesture recognition related to healthcare is a flourishing research domain now-a-days. Parajuli has proposed a method on senior health monitoring using Kinect sensor [7]. The authors have detected the gestures when elders are likely to fall by measuring gait and also analysed the changes in posture from sitting to standing or vice versa. As the skeleton varies widely depending on the viewing angle, thus data is scaled based on subject's height and shoulder width. The recognition stage consists of Support Vector Machine (SVM). The paper lacks in medical knowledge based approach, while our work is not only capable of dealing with healthcare related gestures, but also the soul of the work is based on doctor's advice on identification of physical disorders. Another approach is proposed by Thi-Lan Le for posture recognition for health monitoring framework [8]. The author has extracted the skeletons provided by Kinect for detection of lying, sitting, standing and bending postures. The features used in this paper are the different joint angles and SVM is used as the classifier. Our proposed work recognizes much more complicated gestures than [8] in lesser amount of time. Kinect sensor has also found application of posture recognition in cases like children tantrum analysis [9]. Though the paper proposes a medical knowledge based system, but lacks in dealing with complex body gesture. The paper has limited applications in recognizing trivial body postures like push, shout and attack using k-means clustering, whereas our work deals with complicated body gestures related to muscle and joint problems.

In this paper, Kinect sensor is employed to recognize human body gestures with the help of 20 body joints in 3D. From these 20 joints, (${}^{20}C_2$-19=) 171 Euclidean distances are measured taking two joints at a time (excluding the 19 fixed segments like shoulder-elbow, knee-ankle, etc.). This huge amount of information forms the feature space. To linearly reduce the dimension (as the work should be time efficient), principal component analysis (PCA) is implemented. Due to differences in habits of different individuals based on age, sex and physical built, their gestures for a specific disease vary greatly from each other. This leads to fuzziness of the input. To solve this problem we have incorporated Fuzzy C Means clustering at the recognition stage. The overall accuracy obtained is 96.0201% with time complexity of 0.0439 second in Intel Core i3 processor and 4GB RAM.The paper gives an overview of Kinect Sensor, a description of the healthcare associated gestures and the proposed method for recognizing them in section labelled ‘Materials and Methods’. ‘Results and Discussion’ section contains the experimental results. Finally the work is concluded with the ‘Conclusion’ section by mentioning the provisions for future work.

Materials and Methods

The sensor used for recording gestures, the specifications of the gestures representing various disorders and the various steps of the experiment conducted are discussed in this section.

A. Kinect Sensor

Kinect sensor is a product of an imminent technology which basically looks like a webcam as shown in Figure 1 [4, 5, 6]. It detects the 3D image representation of human being [3]. It tracks the skeleton of the person present in front of it within a finite amount of distance of 1.2 to 3.5 m. It has a set of visible IR and RGB cameras. The images captured by the IR cameras are processed using Kinect Sensor’s Software Development Kit (SDK) which generates the skeleton of the person sensed irrespective of the colour of the person’s attire [10]. The frame rate used for this work is 30 frames per second (fps). Recognition based on the skeleton (joint coordinates) of the subject protects his/her personal details and preserves privacy of the subject while simultaneously requires very less amount of data (20 joint coordinates) to be processed.

Figure 1. Kinect Sensor.

B. Healthcare Associated Gestures

Due to the hectic schedules of young individuals (age group of 20-40 years), foremost amount of time spend by them is in office places. Lack of time in physical activity leads to muscle and joint associated diseases. These diseases can proceed to chronic stages if not treated in early stage. The targeted areas of a few of these frequently observed pains are lower back, knee, calf muscle, shoulder and neck. This paper addresses 12 gestures whose associated diseases are presented in Table I. All the skeletons shown in Table 1 depicts pain in the left side. In this work, C stands for class.

TABLE I. LIST OF GESTURES

Name of Diseases	Pain Position	Body Gesture due to Pain	Sitting Gesture (Class labels)	Standing Gesture (Class labels)
Lumbosacral strain	Lower back	Bends forwards while supporting lower back with both hands.	-	 (C6)
Prolapse intervertebral disc	Lower back	While picking up any fallen item with one hand, supporting lower back with the other.	 (C1)	 (C7)
Knee sprain	Knee	Tries to flex the affected knee and support it with both hands.	-	 (C8)

Gastro-soleus muscle spasm	Calf muscle	Rubbing of the calf muscle in order to get relief.	 (C2)	 (C9)
Rotator cuff tear of shoulder	Shoulder	Massaging shoulder with single hand.	 (C3)	 (C10)
Spasmodic torticollis	Neck	Massaging neck with single hand and other hand supporting the forehead.	 (C4)	 (C11)
Trapezius fibromyalgia	Neck	Massaging neck with single hand.	 (C5)	 (C12)

C. Procedures

The steps of the experiment conducted for gesture recognition and detection of diseases from the recognized gesture are briefly outlined in Figure 2. For dimension reduction linear principal component analysis (PCA) is used, while recognition of gestures is carried out with the help of fuzzy C means (FCM) clustering algorithm on the dataset acquired using the Kinect sensor.

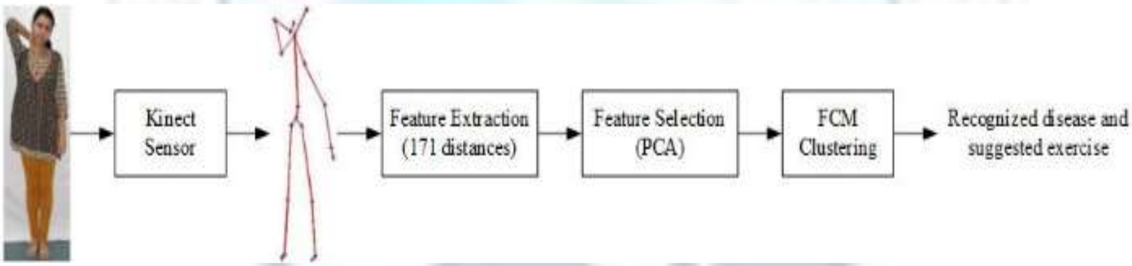

Figure 2. Flowchart of the work.

- **Data Acquisition and Feature Extraction**

Twenty subjects (13 female and 7 male) in the age group of 27±5 years are asked to participate for data acquisition. They are asked to mimic the diseases as instructed using a video stimulus. The stimuli consisted of alternating phases of act (for 2 second) and relax (for 2 second). Skeleton coordinates are acquired using Kinect sensor in the act phases. From the 2 seconds of data or equivalently $2\times30=60$ frames, the 50th frame is selected. This is because the gesture is expected to be achieved towards the end of the 2 second segment. Each gesture is repeated 5 times by each subject. From each of these observations, 171 distances between the different joint coordinates is calculated as the feature vector. These distances are normalized with respect to the maximum value to remove the scaling effect due the variation in the physical built of the different subjects. Thus, a dataset of order $(20\times12\times5)\times171$ is obtained. The gesture where pain occurs in right side is used. However, the distance values of left and right side can be interchanged to detect pain on the other side.Following this, an assessment is conducted to test whether the gestures are overlapping.

For this, at first the mean and standard deviation of the feature vector of all the gestures are constructed. This yields 171-dimensional vectors which are reduced to one dimension by taking their sum across the 171 dimensions. This gives sum of mean features (M) and sum of standard deviation of features (S) for each of the 12 gestures. Now, for every gesture we consider how many other gestures (M of other gestures) falls within $M\pm3\times S$ of that gesture. This gives us a symmetric binary matrix which shows how many gestures are overlapping. The results demonstrate that many of the gestures are overlapping which support our choice of fuzzy clustering.

- **Principal Component Analysis**

Principal component analysis (PCA) [11, 12] is based on orthogonal transformation to reduce dimension in feature space. It based on the idea that the number of principal components is less than or equal to the number of original features. The first principal component is assumed to have the largest possible variance. This analysis is also known as Karhunen-Loève transform. Using this, the 171-dimensional feature space is reduced to d-dimensional feature space, where d is smaller than 171.

Feature selection is primarily of two kinds: wrapper method (which varies feature size according to the performance of a classifier) and filter method (which varies the feature size and tries to maximize the information theoretic content of the dataset). PCA is an unsupervised (does not require the knowledge about different groups or gestures) filter method that exploits the statistical information present within the data to compute a transformation matrix that projects a D-dimensional space (here, D=171) to a d-dimensional space (d<D) as shown by (1).

$$PCA: R^D \rightarrow R^d \qquad (1)$$

The steps of the Karhunen- Loève Transformation (KLT) is briefly summarised, here.

1) For the transposed dataset X having order of feature dimension (D) × number of trials (n), the autocorrelation matrix R_X is computed using (2). Thus, order of R_X is D × D.

$$R_X = \left(\sum_{i=1}^{n} x_i x_i^T \right) \Big/ n = \left(XX^T \right) \Big/ n \qquad (2)$$

2) Eigen values and the corresponding Eigen vectors of R_X are obtained. This gives D Eigen values and D D-dimensional Eigen vectors.

3) d largest Eigen values and their corresponding Eigen vectors are chosen. Thus, we have d D-dimensional vectors $a_1, a_2, \dots, a_d$ which are arranged in the form of a matrix (the transformation matrix) where each column is an Eigen vector. Hence, the order of this transformation matrix is D × d.

4) The dataset X is projected on to a lower d dimensional space spanned by $a_1, a_2, \dots, a_d$. This transformation is done according to (3). Thus, the resultant is a d × n matrix which provides the transposed dataset Y having d as the feature dimension.

$$y_i = a_i^T X \qquad (3)$$

- Fuzzy C Means Clustering

This clustering method based on the assumption that a particular point does not belong to a cluster completely, but with a certain membership value [13] which is between 0 to 1.

Let there be n data points ($X = [x_1\ x_2\ x_3\ \dots\ x_n]$) and c number of cluster ($A = [A_1\ A_2\ A_3\ \dots\ A_c]$). The membership function is denoted as $\mu_{Ai}(x_k)$ and is subjected to the constraint (4). The expression for cluster centre V_i is given by (5). Thus the aim is to minimize the objective function J_m over V_i (for fixed partitions U) and μ_{Ai} (for fixed V_i) where J_m is given by (6). This constrained optimization problem is solved to obtain membership values $\mu_{Ai}(x_k)$ given (7).

$$\sum_{i=1}^{c} \mu_{A_i}(x_k) = 1 \quad \text{for all } k = 1 \text{ to } n \qquad (4)$$

$$V_i = \left[\sum_{k=1}^{n} \left\{ \mu_{A_i}(x_k) \right\}^m x_k \right] \Big/ \left[\sum_{k=1}^{n} \left\{ \mu_{A_i}(x_k) \right\}^m \right] \qquad (5)$$

$$J_m(U, V_i) = \sum_{k=1}^{n} \sum_{i=1}^{c} \left\{ \mu_{A_i}(x_k) \right\}^m \left\| x_k - V_i \right\|^2 \qquad (6)$$

$$\mu_{A_i}(x_k) = \left[\sum_{j=1}^{c} \left(\left\| x_k - V_i \right\|^2 \Big/ \left\| x_k - V_i \right\|^2 \right)^{1/(m-1)} \right]^{-1} \qquad (7)$$

In this work, a data point is said to belong to that cluster for which it has maximum membership. The parameter m deciding the soft clustering margin is chosen to be 1.6 and a maximum of 100 iterations or a minimum J_m of 1e-5 are used as the stopping condition.

Results and Discussions

The results obtained in different stages of the experiment are summarized in this section.

D. Assessing the Fuzziness of the Input

The values of the sum of mean feature (M) and standard deviation (S) of the 12 gestures along with the symmetric binary matrix indicating overlap of different gestures in feature space is shown in Table II. For example, the first row of the binary matrix indicates that gesture 1 overlaps with gesture 2 to 10; the second row indicates that gesture 2 overlaps with gesture 1 and so on. This overlapping tendency of the input ascertains its fuzziness.

TABLE II. MEAN FEATURES, STANDARD DEVIATION AND BINARY MATRIX INDICATING OVERLAPPING GESTURES HAVING FEATURES IN THE RANGE M±3×S OF ONE ANOTHER.

Class	M	S	Binary Matrix											
			C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*
C1	80.30	7.97	1	1	1	1	1	1	1	1	1	1	0	0
C2	72.29	2.91	1	1	0	0	0	0	0	0	0	0	0	0
C3	82.00	3.90	1	0	1	1	1	0	1	1	1	0	0	0
C4	90.38	4.95	1	0	1	1	1	1	1	1	1	1	0	0
C5	88.49	3.09	1	0	1	1	1	0	1	1	1	0	0	0
C6	101.79	3.03	1	0	0	1	0	1	0	0	0	1	0	1
C7	82.69	12.25	1	0	1	1	1	0	1	1	1	1	1	1
C8	88.90	8.79	1	0	1	1	1	0	1	1	1	1	1	1
C9	84.12	3.57	1	0	1	1	1	0	1	1	1	0	0	0
C10	98.78	3.55	1	0	0	1	0	1	1	1	0	1	0	0
C11	115.26	4.11	0	0	0	0	0	0	1	1	0	0	1	1
C12	109.54	4.46	0	0	0	0	0	1	1	1	0	0	1	1

E. Clustering Performance

The dataset is 5-fold cross-validated to obtain 60% of the dataset as the train-set, 20% as the validation-set and the remaining as the test-set. After the train-set is clustered, the cluster centres and the indices representing the cluster to which a given sample belongs are obtained. As we know the class labels, we can determine whether all the samples of a particular class are clustered into the same cluster. If not, the cluster index that occurs most among the samples of a class is treated as the cluster corresponding to that class. Based on the number samples correctly clustered, we obtain the training performance. For any unknown sample (from test-set), the Euclidean distances (although computational expensive yet most precise distance metric) between the test sample and all the cluster centres are measured. The sample belongs to that cluster whose centre has the minimum distance with the unknown sample. As the class to which it should belong is known apriori and the cluster index of that particular class has been just obtained, it is easily identified whether the unknown sample is mapped to the correct cluster. This provides the testing performance. The training accuracy, training time, testing accuracy and testing time are mentioned in Table III. It also mentions the results of clustering without the PCA step and compares these results with the other standard clustering algorithms viz. k-means [14, 15] and k-medoids [16, 17] algorithms.

TABLE III. COMPARISON OF ACCURACY AND TIME (MEAN ± STANDARD DEVIATION) FOR THREE CLUSTERING METHODS.

Clustering Algorithms (feature dimension, d)	Training		Testing	
	Accuracy (%)	*Time (s)*	*Accuracy (%)*	*Time (s)*
FCM (d=171)	95.6250±2.4518	0.0235±0.0027	93.3333±1.9003	0.0335±0.0010
FCM+PCA (d=10)	94.3750±1.3060	0.0510±0.0046	91.5001±2.2361	0.0616±0.0012
FCM+PCA (d=50)	**96.1067±1.8817**	**0.0330±0.0031**	**96.0201±1.8066**	**0.0439±0.0048**
FCM+PCA (d=100)	94.6667±0.5392	0.0324±0.0028	94.1667±1.4907	0.0433±0.0089
FCM+PCA (d=150)	94.5000±0.3486	0.0355±0.0046	93.0000±1.6245	0.0443±0.0058
k–means (d=171)	89.5000±1.086	0.0402±0.0062	88.3333±0.5311	0.0332±0.0012
k-means+PCA (d=10)	92.5000±1.5548	0.0275±0.0014	88.1667±2.2361	0.0329±0.0014
k-means+PCA (d=50)	**94.4583±1.8842**	**0.0323±0.0020**	**93.9999±2.8504**	**0.0374±0.0013**
k-means+PCA (d=100)	86.6250±1.8018	0.0315±0.0003	84.8333±3.2489	0.0397±0.0073
k-means+PCA (d=150)	86.8203±1.3206	0.0336±0.0027	83.6667±1.6029	0.0377±0.0007
k-medoids (d=171)	83.5417±1.4358	0.0046±0.0006	79.6667±2.7386	0.0103±0.0013
k-medoids+PCA (d=10)	82.3621±0.7598	0.0045±0.0006	78.3333±3.3333	0.0099±0.0007
k-medoids+PCA (d=50)	**87.2308±1.0657**	**0.0042±0.0007**	**82.4206±3.2151**	**0.0107±0.0011**

k-medoids+PCA (d=100)	85.4183±0.9256	0.0049±0.0005	81.9245±2.7891	0.0109±0.0025
k-medoids+PCA (d=150)	83.7139±1.4283	0.0052±0.0006	79.3428±2.1342	0.0104±0.0007

From Table III, we can see that for different size of feature subset the accuracy is low for small dimension of feature-space. It peaks at 50 dimension and then gradually decreases. This is because at when the feature dimension is reduced to a very small value like 10, the relevant information are lost. Again, as feature dimension increases to a very high value, the accuracy is hampered due to the presence of redundant information. Thus, a feature dimension around 50 is ideal for this case. It is also noted from Table III that FCM yields the best results as is predicted. This is due to the fuzziness of the input. The highest performance is attained by FCM using the dataset reduced to 50 dimension using PCA providing an accuracy of 96.0201% in 0.0439 second.

F. Performance Analysis: Mc Nemar's Test

McNemar's Test [18] is used to compare two algorithms for assessing which one is better among them. Here, we assume FCM+PCA (d=50) to be the reference algorithm and compare it with either k-means+PCA (d=50) or k-medoids+PCA (d=50) at a time. A contingency table is required for McNemar's Test for comparing algorithms A and B whose symbols and terms are described in Table IV.

TABLE IV. CONTINGENCY TABLE OF MCNEMAR'S TEST.

n_{00}=number of samples mapped to a wrong cluster by both the algorithms A and B	n_{01}=number of samples mapped to a wrong cluster by algorithm A but not by B
n_{10}=number of samples mapped to a wrong cluster by algorithm B but not by A	n_{11}=number of samples mapped to a wrong cluster neither by algorithm A nor by B

According to the null hypothesis, all the classifiers are equivalent and thus, n_{01} and n_{10} are same for all algorithms. In this work, the data-set is 5-fold cross-validated and the algorithms are tested on each fold of the data-set. Thus, 20% of the dataset = 20% of 1200 samples = 240 samples forms the test-set. This is only a portion of the data-set. In order to get full coverage of the data-set the values of the contingency table of the 5-folds of classification are added. McNemar's statistic with one degree of freedom considering the correction factor is given by (8).

$$\chi^2 = \left(\left|n_{01} - n_{10}\right| - 1\right)^2 \Big/ \left(n_{01} + n_{10}\right) \tag{8}$$

The critical value of chi-square for 95% confidence interval is 3.84 for one degree of freedom. If the chi-square value obtained from the contingency table is greater than the critical value $\chi^2_{1,0.05}$ then the null hypothesis is correct only with a probability less than 0.05 (in other words null hypothesis is rejected for 95% confidence interval). The values of the parameters from contingency table used in the test, the obtained chi-square values and the acceptance or rejection of null-hypothesis are indicated in Table V.

TABLE V. STATISTICAL TEST: MCNEMAR'S TEST.

Reference Algorithm (A) = FCM + PCA				
Classifier Algorithm used for comparison (B)	**Parameters for McNemar's Test**		χ^2	**Acceptance/ Rejection of null hypothesis**
	n_{01}	**n_{10}**		
k-means + PCA	21	39	4.8167	Rejected
k-medoids + PCA	27	56	9.4458	Rejected

According to Table V, for both the cases the null-hypothesis is rejected. Hence, the algorithms are not equivalent. Moreover, n_{01} is lesser than n_{10} for both the cases. This indicates that algorithm A i.e. FCM + PCA (d=50) is a much more robust algorithm than k-means or k-medoids algorithms. This validates our results and also our claim that FCM is a better choice of recognition algorithm for this application.

G. Comparison with previous works

The bar graph in Figure 3 illustrates that our proposed work clearly outperforms the previous algorithms used in [7, 8, 9] when applied on our dataset.

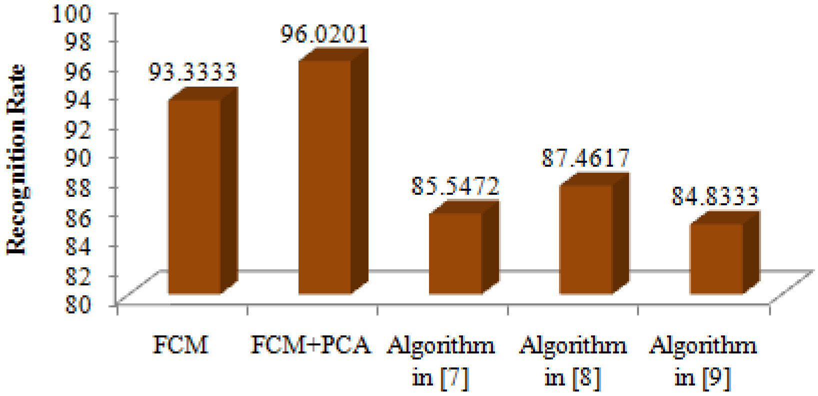

Figure 3. **Comparison of accuracy rates with previous works**.

Conclusion

This paper explains a novel approach to recognize 12 gestures arising from pain and stiffness in joint and muscles. Due to the working nature of humans in several companies, these diseases occur and can progress to severe stage if not detected at an early stage. As the same gesture depicting the onset of a particular disease varies widely across different subjects, thus, the input is fuzzy in nature. Hence, fuzzy clustering is used for gesture recognition. This work elaborates a method to recognize the early stage gestures related to healthcare in young person using FCM clustering with accuracy of 96.0201% in 0.0439 second obtained using a dataset whose dimension is reduced from 171 to 50 using PCA. This algorithm is shown to be better than other standard clustering algorithms using McNemar's Test. Also, the proposed algorithm provides better result than the previously proposed algorithms for gesture recognition.

In future, we are trying to build a much more complicated system with more body gestures arising from working habits of different individuals such that this work has wide range of implementations in any office premises to alert the employees about their decaying health. As a whole, the proposed work is based on medical knowledge acquired from doctors. None of the paper till date shows better result than this work with such complex body gestures associated with young people's healthcare.

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