A Novel Gesture Recognition System Based on Fuzzy Logic for Healthcare Applications

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***Abstract*—This work demonstrates an interesting approach to gesture recognition for elderly people for the purpose of health monitoring at home. The system proposes to detect disorder symptoms on the basis of gesture analysis and generate alarms, thereby finding significance in elderly healthcare. Here the gestures are tracked using Microsoft's Kinect sensor. From each frame captured by the Kinect sensor, four centroids representing four parts of the body are calculated and from these four centroids a novel feature set is extracted in terms of Euclidean distances and angles. We have noticed that for different persons' body types the extracted features might vary. Thus to accommodate these non-uniformities, we have used the concept of interval type-2 fuzzy logic based classification. The unknown gesture is recognized based on matching with all the known gestures from the dataset. The proposed methodology provides a high accuracy rate of 92.14%.**

Keywords*—*Healthcare; interval type 2 fuzzy set; Kinect sensor

I. Introduction

Non-vocal communication with the help of noticeable body movements to generate certain messages are known as gestures. The body parts involved in producing such meaningful information are the face, arms and head. Interaction between humans, environment and computers are the areas where body language detection finds significance. The present work explores gesture recognition related to physical ailments in elderly people from three dimensional body joint co-ordinate data analysis.

The medical disorders considered for this work are identified by the symptoms shown by elderly persons mainly due to muscle and joint pains. A few of the several causes of these disorders are injury, fatigue, and aging; and the disorders are further intensified due to sedentary lifestyle of the individuals. The suggested system can be used for health monitoring of the elder people at their homes. Early stage recognition of the disorders from the symptoms using the proposed approach can prevent further serious developments of the disorders in the elder individuals.

Microsoft's Kinect sensor [1]–[3] has found significant importance in a wide variety of applications related to gesture recognition over the last few years. Among the several works from the literature, one interesting work is done using a neural network optimized by Levenberg-Marquardt learning rule (LMA-NN) where muscle and joint pain related disorders are processed for elderly healthcare [4]. Another work [5] deals with ensemble decision tree for fall detection using the depth map processing obtained from Kinect sensor. Another paper proposes an approach to gesture recognition for Parkinson's disease using the Kinect sensor [6]. Here Kinect sensor along with an infrared camera Vicon system is implemented to measure the proximity of hand movement. The Kinect sensor finds wide applications in upper limb rehabilitation [7]. Such systems are suitable for home-based motion capture by measuring finger joint kinematics.

Oszust *et al.* [8] have proposed a method for recognition of signed expressions observed by the Kinect sensor. Here skeletons of human body with shape and position of hands are taken into account for polish sign language recognition. The recognition is implemented using k-nearest neighbor (kNN) classifier. Burba *et al.* [9] have used Microsoft Kinect to monitor respiratory rate is estimated by measuring the visual expansion and contraction of the user's chest cavity. This work also lightens the area of measuring fidgeting behavior. This is also done by Kinect sensor focusing on vertical oscillations of the user's knees. Brain mapping is also possible using Kinect sensor along with EEG from human brain [10].

Our simple and cost effective system is divided into three major stages. In the first stage, the Kinect sensor [1]–[3] recognizes the human body using twenty joint co-ordinates in three dimensions (3D). From these twenty joints, four centroids are evaluated which represent the left arm, right arm, left leg and right leg body parts for any gesture. In the next stage, six Euclidean distances are measured between four centroids taking two at a time. These distances form the feature space in this work. The final stage is for matching of an unknown gesture with six known gestures. We have created 3 datasets by acquiring data from Jadavpur University research scholars. Each dataset comprises of data from 30 subjects and 10 instances of each gesture are performed by each subject. This is done to incorporate the variations involved in same gesture due to subjects' height, weight and body type. Next a novel interval type-2 fuzzy set (IT2FS) [11]–[13] based recognition system is designed to deal with the fuzziness or variations in the dataset.

978-1-5090-0626-7/16/$31.00 ©2016 IEEE

Statistical tests are under taken into account for the reliability of the hybrid system for gesture recognition.

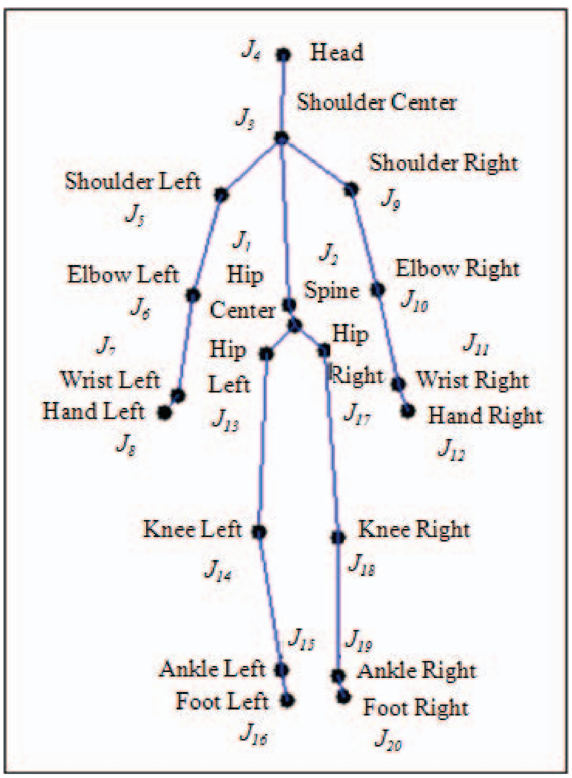
The rest of the paper is structured as follows. Section II introduces the proposed methodology including explanation on Kinect Sensor, concerned disorders and work flow of proposed system. Section III describes the experimental results and justifies our work by performance analysis and statistical tests. Finally section IV concludes the paper.

II. Methodology

This section introduces the basics of the Kinect sensor along with the three stages required for gesture recognition.

A. Kinect Sensor

The Kinect sensor [1]–[3] along with the associated Software Development Kit (SDK) tracks the human motion by generating a skeleton with three dimensional co-ordinates within a finite range of distance (roughly 1.2 to 3.5m). This is achieved using the visible IR (which is the depth sensor, by which z direction value for each joint is obtained) and RGB cameras. The skeleton produced by the Kinect sensor has twenty body joints. Fig.1 shows all the joints along with the index J_i ($1 \leq i \leq 20$) of the human body considered in the skeleton. The Kinect has a sampling rate of 30 frames per second. The background, dress color and lighting of the room are irrelevant for skeleton detection using the Kinect sensor. Hence it can recognize human motion in a very wide range of surrounding physical conditions.



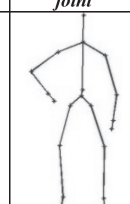
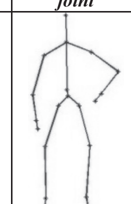
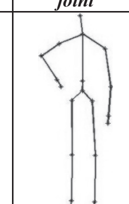
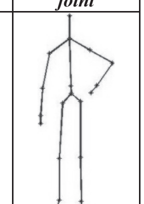
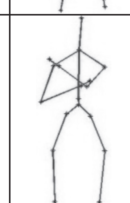
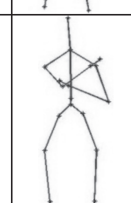
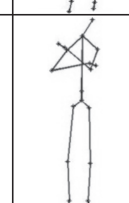
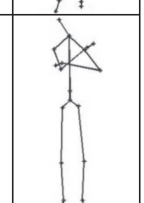
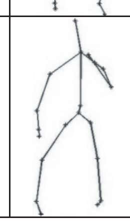
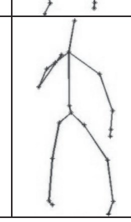
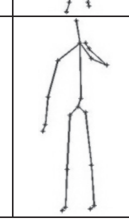
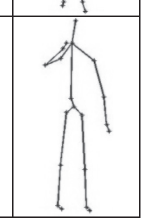
Twenty body joints captured using Kinect sensor.

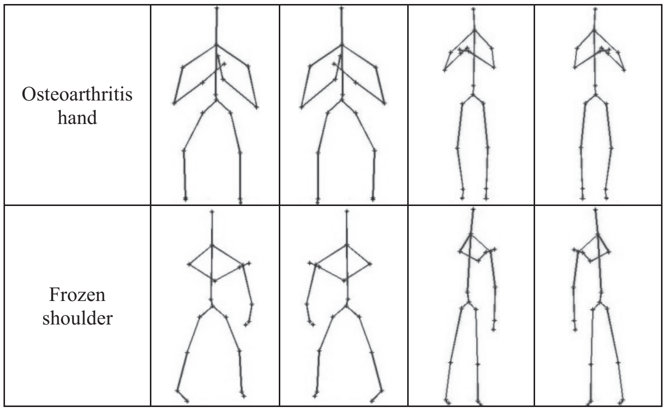
B. Disorders Considered for Proposed System

The disorders taken into account for this proposed work are usually prevalent in elderly individuals. We have processed 20 (considering each pain in both parts of the body) gestures that correspond to the symptoms shown in such disorders. The RGB (only for pain at right joint) and skeletal images corresponding to the gestures are given in Fig. 2 and Table I respectively. The names of the concerned disorders are also given in the table.

Fig. 1. Selected RGB images for the concerned disorders.

TABLE I. Skeletal Images for The Concerned Disorders

Disorder name	**Skeleton image from Kinect sensor**			
	While sitting		***While standing***	
	Pain at right joint	***Pain at left joint***	***Pain at right joint***	***Pain at left joint***
Lumbar spondylosis				
Tennis elbow				
Cervical spondylosis				



C. Description of the Proposed System

The three stages of the proposed system are illustrated in Fig. 3.

1) Centroid Calculation

Four centroids are calculated for each frame representing the four body parts. The coordinate matrix (*COM*) containing the joint co-ordinates for a frame is given in (1). Here each row contains the 3-dimensional co-ordinates for each of the twenty body joints and each column depicts a specific dimension.

$$COM = \begin{bmatrix} J_1(x) & J_1(y) & J_1(z) \\ J_2(x) & J_2(y) & J_2(z) \\ \dots & \dots & \dots \\ J_{20}(x) & J_{20}(y) & J_{20}(z) \end{bmatrix} \tag{1}$$

The joints according to row are hip center, spine, shoulder center, head, shoulder left, elbow left, wrist left, hand left, shoulder right, elbow right, wrist right, hand right, hip left, knee left, ankle left, foot left, hip right, knee right, ankle right and foot right in order numbered in the suffix from 1 to 20.

Now from this matrix, we obtain four centroids from the arm and leg joints. The centroids are calculated using the following four equations (2-5).

$$C_{LA} = \frac{J_5 + J_6 + J_7 + J_8}{4} \tag{2}$$

$$C_{RA} = \frac{J_9 + J_{10} + J_{11} + J_{12}}{4} \tag{3}$$

$$C_{LL} = \frac{J_{13} + J_{14} + J_{15} + J_{16}}{4} \tag{4}$$

$$C_{RL} = \frac{J_{17} + J_{18} + J_{19} + J_{20}}{4} \tag{5}$$

where *RA*, *LA*, *RL* and *LL* stands for right arm, left arm, right leg, left leg respectively. Fig. 4 depicts the four centroids using red squares. As for this proposed work, first four joints (J_1-J_4) are not required, thus the circles for these joints are not filled.

2) Feature Extraction

From the four centroids, we have calculated six Euclidean distances (${}^4C_2$=6) by taking two centroids at a time according to (6-11). Also four angle values are measured using (13-16).

$$f_1 = \text{Euclidean\_dist}\left(C_{LA}, C_{RA}\right) \tag{6}$$

$$f_2 = \text{Euclidean\_dist}\left(C_{LA}, C_{RL}\right) \tag{7}$$

$$f_3 = \text{Euclidean\_dist}\left(C_{LA}, C_{LL}\right) \tag{8}$$

$$f_4 = \text{Euclidean\_dist}\left(C_{RA}, C_{RL}\right) \tag{9}$$

$$f_5 = \text{Euclidean\_dist}\left(C_{RA}, C_{LL}\right) \tag{10}$$

$$f_6 = \text{Euclidean\_dist}\left(C_{RL}, C_{LL}\right) \tag{11}$$

where Euclidean_dist function evaluates the Euclidean distances between the two variables. As the variations of persons' height, weight and body type variation may lead to erroneous results, thus while creating the feature vector, we incorporate normalization of the features using (12). Here, $f_{i,j}$ denotes the j^{th} instance of the i^{th} feature and $f_{i,max}$ and $f_{i,min}$ denote the maximum and minimum values of that feature respectively. All the six features are explained in Fig. 5(a).

$$f_{i,j} \leftarrow \frac{f_{i,j} - f_{i,\min}}{f_{i,\max} - f_{i,\min}} \tag{12}$$

$$f_7 = \text{Angle}\left(C_{LL}, C_{LA}, C_{RA}\right) \tag{13}$$

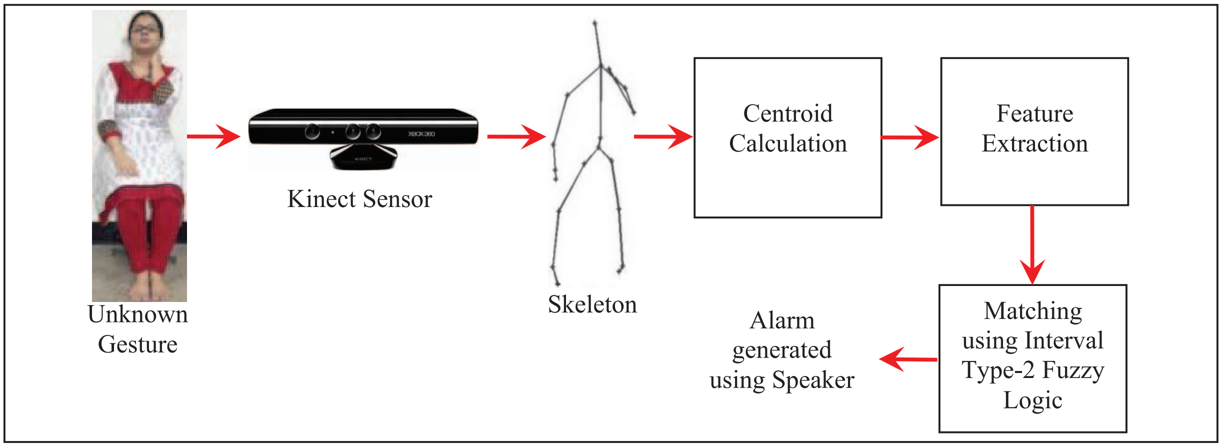


Fig. 2. Flowchart of the proposed system.

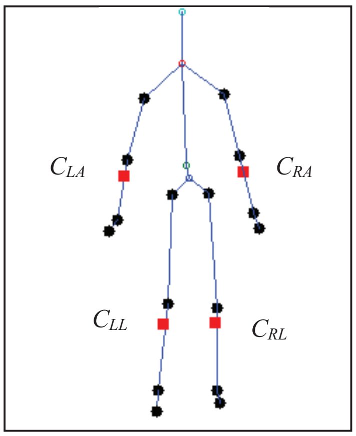


Fig. 3. Four centroids.

$$f_8 = \text{Angle}\left(C_{LA}, C_{RA}, C_{RL}\right) \tag{14}$$

$$f_9 = \text{Angle}\left(C_{RA}, C_{RL}, C_{LL}\right) \tag{15}$$

$$f_{10} = \text{Angle}\left(C_{RL}, C_{LL}, C_{LA}\right) \tag{16}$$

where Angle function calculates the angle made by the three centroids taken in the argument, at the middle centroid. Fig. 5(b) shows the four angle features.

3) Matching using IT2FS

As the subjects' heights, weights and body types influence the feature space up to a large extent, thus to deal with the irregularities or variations in these, fuzzy logic can be incorporated for classifying the gestures. Type-1 fuzzy systems (T1FS) can be used for classification by representing the variations in data at different instances using a single membership function. However, experimental data taken at different times vary from each other and also there are variations for data from different persons. T1FS is unable to capture the variations in the memberships for different trials of the same experiment over a period of days or over different subject datasets. Interval Type-2 Fuzzy Systems (IT2FS) [11]–[13] can overcome this difficulty.

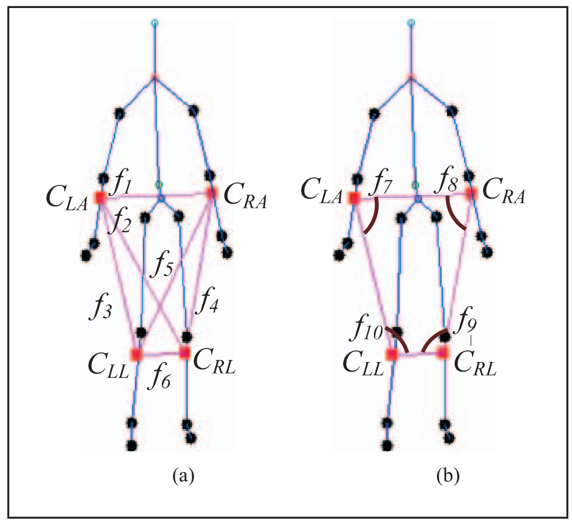


Fig. 4. Ten features, (a) for Euclidean distances, (b) for angles.

In a normal or Type-1 Fuzzy System (T1FS) every variable has a membership value in the closed interval [0,1] according to a predefined membership function. Given a set of variables, the Gaussian membership function $m(x)$ of a variable x is easily determined from their mean μ and the standard deviation σ according to (17), and is implemented in classification problems.

$$m(x) = \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{17}$$

In interval type-2 fuzzy sets (IT2FS), we take union of all the primary memberships (i.e., memberships for T1FS) for similar set of observations to form a region called the footprint of uncertainty (*FOU*). The minimum and maximum values of the primary memberships over all observations forming the *FOU* are treated as lower membership function (*LMF*) and the upper membership function (*UMF*) respectively. In IT2FS [11] the secondary membership function is uniform and assumes a constant value of 1 for all values of $m(x)$ in between the *LMF* and *UMF* and 0 otherwise.

Suppose in a dataset, we have P number of subjects and each subject is performing a specific gesture for Q number of times. Now if we have Z number of disorders concerned, then for a specific disorder k ($1 \le k \le Z$), for the i^{th} feature and for subject n ($1 \le n \le P$), we have Q number of data points $f_{1,i}^{n,k}$, $f_{2,i}^{n,k}$, …, $f_{Q,i}^{n,k}$. For these Q data points, we determine the Gaussian memberships and form a Gaussian curve $m(f_i^{n,k})$. Similarly, we generate P number of Gaussian curves for each disorder and each feature (i), where $1 \le i \le 10$. This procedure is elaborated in Fig. 6.

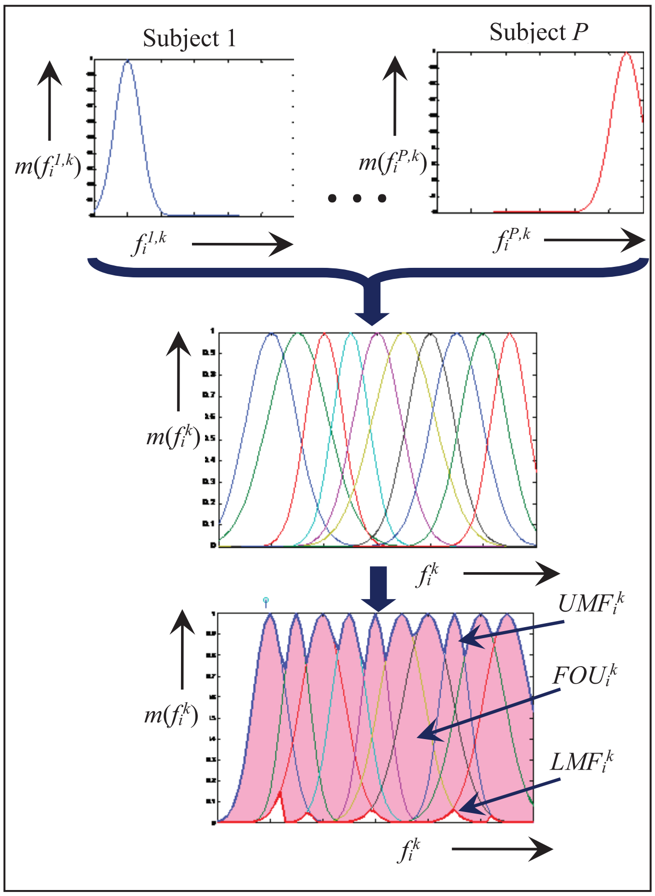


Fig. 5. FOU calculation for i-the feature.

Here we have Z classes (number of disorders = number of classes). For the i^{th} feature, considering the minimum and maximum values of features over the observations over all subjects, the primary memberships, and consequently the LMF_i^k, UMF_i^k and FOU_i^k are constructed. Say, a feature vector $f^{unknown}$ corresponding to an unknown dataset has to be classified. Each component $f_i^{unknown}$ ($1 \le i \le 10$) is projected on the corresponding FOU_i^k to find the intersections with the LMF_i^k and UMF_i^k of that component to obtain $\overline{LMF_i^k}$ and $\overline{UMF_i^k}$. For a particular class k, the fuzzy T-norm (implemented by taking the minimum) of all $\overline{LMF_i^k}$ and that of $\overline{UMF_i^k}$ for $1 \le i \le 10$ are computed to obtain the LMF_T^k and UMF_T^k respectively. Using these values the strength S^k of the class k is determined by the computation of the centroid given by (18). Computing the strengths of all the classes, the class having the maximum strength is determined to be the class of the test sample.

$$S^k = \frac{UMF_T^{\ k} + LMF_T^{\ k}}{2} \tag{18}$$

III. Experimental Results

For the purpose of this proposed work, we have created three datasets from Jadavpur University research scholars of age group 25-30, 30-35 and 35-40 years. Here each dataset comprises data from 30 subjects and data for each class is collected from each subject for 10 times. From this large dataset, we have randomly selected 500 gestures for testing purpose.

Fig. 7 elaborates the RGB and skeleton of an unknown gesture. It also gives a clear view of the four centroids needed for this proposed work for this test sample. The 3D for twenty joints are given in Table II. The four centroids obtained after processing joints information are also shown in Table II.

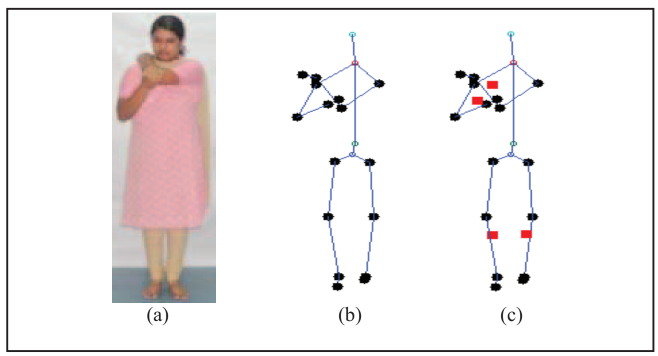


Fig. 6. Unknown gesture: (a) RGB and (b) skeleton of unknown gesture, (c) four extracted centroids.

Table III essays the total procedure for matching using IT2FS technique. This table also provides all the features obtained for unknown gesture. The FOU generated from 30 subjects for known gesture Tennis elbow while the subject is standing and pain is at right side of the body (here it is elbow) for 9^{th} feature is given in Fig. 8. The strength of matching is obtained as 0.2468 and it is the highest strength achieved, so the unknown gesture is treated as Tennis elbow.

While matching by IT2FS, we have introduced a threshold value for strength. If an unknown gesture is showing less than that value, then that gesture is rejected and treated as non-disordered gesture. This value is obtained empirically as 0.2. This is done to neglect the adverse effect of false recognition.

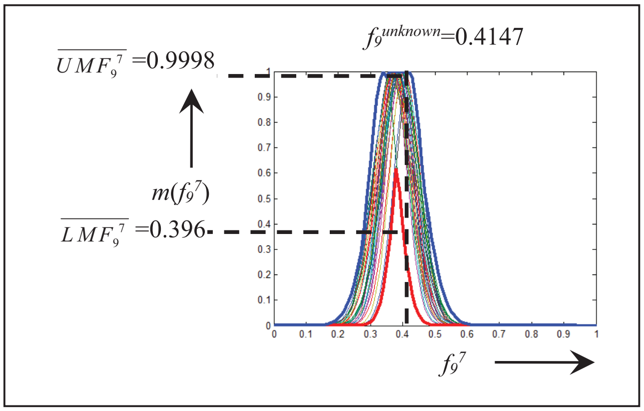


Fig. 7. Calculation of *LMF* and *UMF* for unknown gesture with known Tennis elbow gesture.

A. Performance Analysis

The performance of the proposed system is scrutinized with respect to three datasets already stated with five other known techniques. The other methods are T1FS [14], [15], support vector machine (SVM) [16]–[18], *k*-nearest neighbor (*k*NN) [8], [19], ensemble decision tree (EDT) [5], [20] and Levenberg–Marquardt algorithm induced neural network (LMA-NN) [5]. T1FS is done based on Gaussian membership function. SVM has been used with a radial basis function (RBF) kernel whose kernel parameter has a value 1 and a cost value of 100. *k*NN has been used with *k*=5, Euclidean distance as the similarity measure and majority voting to determine the class of the test samples. Ensemble decision tree classifier is used based on the principle of adaptive boosting taking maximum iterations as 100. For LMA-NN the number of neurons in the intermediate layer is taken as 10, the value of the blending factor between gradient descent and quadratic learning as 0.01, the increase and decrease factors of the blending factor as 10 and 0.1 respectively and the training stopping condition is taken as the attainment of minimum error gradient value of 1e-6.

The performance metrics include precision, recall, accuracy and F1 score. Based on these performance metrics, a comparison among the six gesture recognition algorithms is provided in Fig. 9.

TABLE II. CO-ORDINATE MATRIX FOR THE UNKWNOWN GESTURE OF FIG. 7

Joint	*x* co-ordinate	*y* co-ordinate	*z* co-ordinate		
J_1	-0.0279	-0.1686	2.7447		
J_2	-0.0186	-0.1068	2.8289		
J_3	-0.0195	0.3502	2.9728		
J_4	-0.0296	0.5138	2.9815	**Centroid**	**3D co-ordinate**
J_5	-0.1792	0.2298	2.8412	C_{LA}	-0.1625 0.1332 2.6841
J_6	-0.2591	0.0443	2.7531		
J_7	-0.1276	0.1150	2.5894		
J_8	-0.0840	0.1438	2.5528		
J_9	0.08437	0.2358	2.8112	C_{RA}	-0.1006 0.2212 2.7385
J_{10}	-0.0710	0.0963	2.6485		
J_{11}	-0.1782	0.2669	2.7293		
J_{12}	-0.2378	0.2857	2.7649		
J_{13}	-0.1023	-0.2088	2.6899	C_{LL}	0.0378 -0.6214 2.7129
J_{14}	-0.1289	-0.5228	2.6698		
J_{15}	-0.0859	-0.8631	2.7925		
J_{16}	-0.0920	-0.9195	2.7388		
J_{17}	0.0424	-0.2156	2.7595	C_{RL}	-0.1023 -0.6285 2.7227
J_{18}	0.0612	-0.5227	2.6887		
J_{19}	0.0275	-0.8634	2.7436		
J_{20}	0.0201	-0.8839	2.6598		

TABLE III. CALCULATION OF STRENGTH FOR UNKNOWN GESTURE WITH KNOWN TENNIS ELBOW GESTURE

Features		$\overline{LMF_i^k}$	$\overline{UMF_i^k}$	LMF_T^7	UMF_T^7	S^7
f_1	0.0000	0.1450	0.9949	0.1053	0.3882	0.2468
f_2	0.9005	0.2013	0.5132			
f_3	0.8785	0.1110	0.6053			
f_4	1.0000	0.1053	0.5886			
f_5	0.9940	0.1438	0.4155			
f_6	0.0274	0.2457	0.8342			
f_7	1.0000	0.1587	0.3882			
f_8	0.0000	0.1456	0.5724			
f_9	0.4147	0.3960	0.9997			
f_{10}	0.5107	0.1310	0.9996			

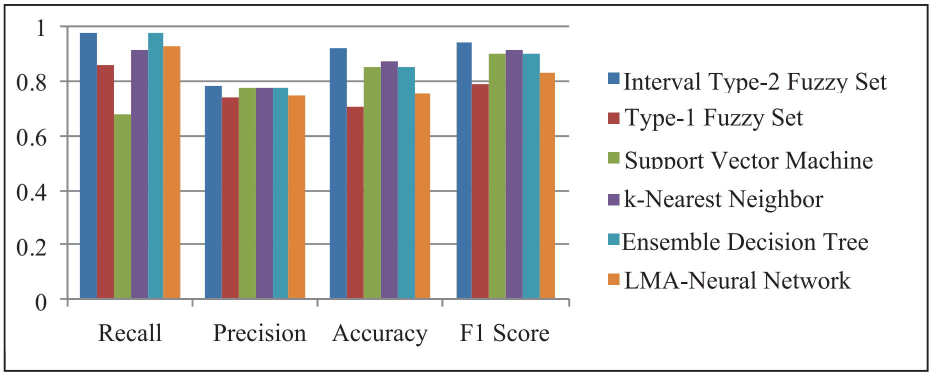


Fig. 8. Comparison of six different techniques.

B. *Statistical tests*

Two statistical tests are performed for judging the performance of our proposed system.

1) *McNemar test*

Let f_A and f_B be two classifiers obtained by algorithms A and B, when both the algorithms have a common training set R. Let n_{01} be the number of examples misclassified by f_A but not by f_B, and n_{10} be the number of examples misclassified by f_B but not by f_A [21]. The validation metric is given by (19).

$$Z = \frac{(|n_{01} - n_{10}| - 1)^2}{n_{01} + n_{10}} \tag{19}$$

Let A be the proposed algorithm and B is one of the other five algorithms. In Table IV, the null hypothesis, claiming the equality of the classifiers under test, has been rejected in most of the cases, as Z>3.841, where 3.841 is the critical value at probability of 0.05. This test is under taken for the 3rd dataset (age group 35-40 years).

TABLE IV. PERFORMANCE ANALYSIS USING MCNEMAR'S TEST

B	***A*= IT2FS**		
	n_{01}	n_{10}	**Z**
T1FS	25	33	0.8448
SVM	23	43	4.5156
kNN	25	49	7.1486
EDT	14	44	14.5000
LMA-NN	17	49	14.5606

2) *Friedman Test*

Of the C algorithms under consideration, the average ranking acquired by the c^{th} ($1 \le c \le C$) algorithm over all d ($1 \le d \le D$) datasets is defined as R_c. The Friedman's statistic given by (20) follows a χ^2 distribution with a degree of freedom equal to C–1.

$$\chi^2 = \frac{12D}{C(C+1)}\left[\sum_{c=1}^{C} R_c^2 - \frac{C(C+1)^2}{4}\right] \tag{20}$$

Here, D=number of datasets considered=3 and C=number of algorithms=6. In Table V, it is shown that the null hypothesis has been rejected, as 13.8571 is greater than the critical value (i.e., 11.070) of the χ^2 distribution for $C-1=5$ degrees of freedom at probability of 0.05 [22]. Here, the rank R_c is taken based on accuracy.

TABLE V. PERFORMANCE ANALYSIS USING FRIEDMAN TEST

Algorithm	**Research scholars of age 25–30**	**Research scholars of age 30-35**	**Research scholars of age 35-40**	R_c	χ^2
IT2FS	1	1	1	1.0000	13.8571
T1FS	6	6	6	6.0000	
SVM	3	5	5	4.3333	
kNN	2	2	2	2.0000	
EDT	4	3	3	3.3333	
LMA-NN	5	4	4	4.3333	

IV. CONCLUSION

Gesture recognition based on disease symptoms to detect the possibility of physical disorders is a novel area of research. Such a study is bound to aid the development of sophisticated health monitoring systems that can be installed at homes or offices and continuously evaluate the presence of a disorder in a person. Elderly healthcare based on home gesture recognition using a Kinect Sensor has gained significant importance. In this work we have successfully demonstrated the use of an interval type-2 fuzzy logic based classifier for gesture recognition in elderly healthcare from data acquired using a Kinect Sensor. While there are several instances of standard pattern classifiers being used in gesture recognition problems, the inherent drawbacks of such algorithms in the inability to handle variations or uncertainties in data taken at different days or across different subjects forbid their use in real life problems. IT2FS provides a simple solution to this problem while overcoming also the problems associated in T1FS based classifiers. The present problem shows recognition accuracy as high as 92.14% using the proposed approach. For gesture recognition, features based on Euclidean distances and angles between four centroids of the body evaluated using mathematical formulations, have been utilized. The performance of the proposed approach has been compared with several standard pattern classification algorithms on the basis of different performance metrics revealing the superiority of the proposed method. The results have been validated through statistical tests as well.

ACKNOWLEDGMENTS

The research work is supported by the University Grants Commission, India, University with Potential for Excellence Program (Phase II) in Cognitive Science, Jadavpur University and University Grants Commission (UGC) for providing fellowship to the author.

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