Fall Risk Assessment Using Fuzzy C Means Clustering Algorithm on Sample Entropy Measure of the Location of Center of Pressure

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Abstract

Fuzzy C means clustering algorithm has been used to predict the probability of fall in elderly. The sample entropy measure of the time series of the location of the center of pressure for closed eye and opened eye standing on the force plate have been considered as effective fall risk factors. All the possible combinations of these factors in opened eyes, closed eyes, and the mixture of these two modes have been discussed. The best combination of the factors that leads to minimum prediction error is reported.

Keywords: Fuzzy C means clustering, fall risk assessment, sample entropy.

Introduction

One of the major life threatening dangers to the elderly is falling which often followed by serious injuries like hip fracture, hospitalization and even death. [1] Unfortunately, the risk of falling is considerably high in older people such that more than one third of adults older than 65 experience at least one fall every year. [2] In 2010, there was about 21,700 fatal falls in elderly and 2.3 million nonfatal falls causes injuries that should be treated in emergency and more than 662,000 of those people were hospitalized. [3] The medical costs for falling are also incredibly high. In 2000, the direct medical costs associated with 10300 fatal falls were $0.2 billion dollars and those for treatment of 2.6 million non-fatal fall injuries were $19 billion dollars. The costs for non-fatal injuries included hospitalizations, (63% or $12 billion), emergency department visits (21% or $4 billion), and treatment in outpatient settings (16% or $3 billion).[4] Moreover, the experience of fall develops a fear that prevent them from their normal activity and exercise that can even increase the risk of falling. [5]

These costs and effects of falling motivate researchers in different areas of expertise to focus on fall risk assessment. The first step in predicting fall is to extract the factors that may have contribution to falling. In [6] it is proposed that the gait cycle abnormality can be considered as a factor affecting the fall risk. Hausdorff et al. have shown that the gait parameters are more variable in community-living elderly who experience falls. [7] Also it is proposed by Maki that although the average gait parameters are related to the fear of falling, the variability of walking features between two strides in a person can be a sign of future falling.[8]

Besides the gait parameters, many other factors are considered as a potential factor for fall prediction in the literature. In [9] age, diabetes mellitus, a history of falling, and treatment with neuroleptics or oral bronchodilators is proposed to be the most important fall risk factors. The effect of visual measures like high and low contrast visual acuity, edge contrast sensitivity, depth perception, and visual field size is considered in [10]. De Boer et al. have shown that the impaired vision can be considered as an independent risk factor for recurrent falling. [11]

Another important factors that have contribution in maintaining balance are center of mass (COM) [12] and center of pressure (COP) [13]. However, even in a young healthy individual who is standing still, the location of the COP has fluctuations with respect to a global coordinates. [14] Thus, extracting information from the time series of the location of the center of pressure is challenging. In [14], the fluctuation of the COP is assumed to be a combination of deterministic and stochastic signals in hope to achieve a better understanding of the postural stability.

One way to analyze a time series signal is to exploit nonlinear measures like approximate entropy(ApEn) or sample entropy (SpEn) to estimate the regularity of signal. Riva et, al. used harmonic ratio (HR), index of harmonicity (IH), multiscale entropy (MSE) and recurrence quantification analysis (RQA) as nonlinear measures to analyze trunk acceleration signal and employed the result of analysis as a fall prediction factor. [15]

Based on the works previously have done for fall prediction, it is obvious that the problem depends on many different factors. Even all the effective factors have not been discovered yet which increases the uncertainties of results. In this type of problems, fuzzy systems are proved to be helpful. Fuzzy logic concept is similar to the human thinking style. It is in the form of fuzzy IF-THEN rules, which are written with linguistic variables and different membership functions. These fuzzy IF-THEN rules characterize simple relationships between fuzzy variables. [16] Mamdani proposed a method based on fuzzy inference systems (FIS) by synthesizing a set of linguistic control rules obtained from experienced human operators, to control engine and boiler combination. [17]

This paper is based on the data collected in an experiment on 101 subjects between 56 to 90 years old. The data contains the time series of the location of the center of pressure measured by force plate in two different cases, the subject stands on the force plate with opened eyes and closed eyes. The sample entropy of these signals are calculated by two different embedding dimensions. These parameters are considered as fall risk assessment factors and used to train and test a fuzzy system using clustering method. 85% of the data used for training and 15% of the data used to test the performance of the trained system.

Theory:

In this article, Fuzzy C means method has been used for clustering, which allows one piece of data to belong to two or more clusters. Fuzzy C means method was introduced in 1973 by Dunn for the first time and was improved by Bezdek in 1982 [18, 19], which is based on minimizing the following objective function.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \qquad 1 \leq m < \infty \tag{1}$$

Where x_i is the i^{th} measured data, u_{ij} is the degree of membership of x_i in the cluster j, c_j is the location of the center of the j$^{\text{th}}$ cluster and m is a real number greater than one.

Using an iterative optimization algorithm on the objective function by updating the membership u_{ij} and the cluster centers c_j, fuzzy partitioning is carried out as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{2}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{3}$$

The iterations will continue until $\max_{ij} \left(\left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right) < £$, which k is the iteration step and £ is a termination criterion between 0 and 1. This procedure will converge to a saddle point of J_m or a local minimum. FCM uses the following steps to calculate cluster's centers c_j in membership matrix U :

1- *Initialize* $U = [u_{ij}]$ *(membership matrix with random components between 0 and 1),* $U^{(0)}$

2- *At k-step: calculate the cluster's center vector* $C^{(k)} = [c_j]$ *with* $U^{(k)}$ *using equation*(3).

3- *Update* $U^{(k)}, U^{(k+1)}$ *using equation*(2).

4- *If* $\left\| U^{(k+1)} - U^{(k)} \right\| < \pounds$ *then stop, otherwise return to step and repeat again*.

Now that the clusters are defined, the outputs associated with the data points in each cluster are grouped as an output set. Each cluster can be expressed as one standard *If-Then* rule which expressed the relation between the data in each cluster with its output set. The general input-output relation can be found by defining a *fuzzy inference engine* using all of these *If-Then* rules. The produced *fuzzy inference system (FIS)* is a function that fits the input-output data. [16] In this paper, we employed *Mamdani* inference engine with *min* as and method, *max* as or method, *min* as implication method and *max* as aggregation method.

Methodology:

Too many factors have been investigated as effective factors for fall risk assessment. Here, the effects of 8 of these factors have been discussed. Table 1 show the factors, which are discussed in this research.

Table 1- list of factors which are discussed in this article

Factor Name
sample entropy_force plate_ center of pressure_eye open_X1
sample entropy_force plate_ center of pressure_ eye open _Y1
sample entropy_force plate_ center of pressure_ eye open _X2
sample entropy_force plate_ center of pressure_ eye open _Y2
sample entropy_force plate_ center of pressure_eye close_X1
sample entropy_force plate_ center of pressure_eye close_Y1
sample entropy_force plate_ center of pressure_eye close_X2
sample entropy_force plate_ center of pressure_eye close_Y2

As it is shown in table 1, the factor which is used is the sample entropy of the time series signals associated with the x and y components of location of the center of pressure measured by force plate in two different states that the subject stands eyes are open and eyes are closed.

Sample entropy (SpEn) is a measure of the complexity of a time series. It is a measure to quantify unpredictability of the signal. For any time series, considering a *template* vector of sequential data points with length *m*, which is called *embedding dimension,* and a tolerance *r*, we call another *m*-dimensional vector of forward sequential points a *match* to the template vector if its maximum element-wise deviation from the template vector is less than *r*. Then the sample entropy is defined as

$$SpEn = -\ln \frac{C^{m+1}(r)}{C^{m}(r)}, \tag{4}$$

where $C^{m}(r)$ is the number of matched pairs with length *m* within tolerance *r*, for every possible *m*-dimensional template vector. The smaller the SpEn is the closest $C^{m}(r)$ and $C^{m+1}(r)$ are. It means that small sample entropy shows that the time series is more regular. [20]

For each case, the sample entropies are calculated with two different embedding dimensions m=2 and m=3 with the same tolerance r=0.25 in each case. These data and also number of falls in the past 12 month have been recorded for a case study contains 101 people with different ages between 56 and 90. Since the maximum number of falls for this group is 5 times in the past 12 month, the following equation has been used to determine the membership function of each person, which indicates how much faller that person is

$$O^{(i)} = \frac{N_i}{\max(N)} \tag{5}$$

where N_i is the number of falls for the i^{th} person participated in the study and N is the maximum number of falls. . First, each of the effective parameters has been considered independently, and then any possible combinations of these parameters (up to all 8 parameters) have been discussed. The total number of different combination of parameters, which have been studied in this article, is 255.

85 percent of whole case study data has been used to train the fuzzy inference system and 15 percent of the data is used as the test data. To evaluate the effectiveness of each combination of parameters, root mean square error (RMSE) has been used as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left[O(P^{(i)}) - O^{(i)}\right]^2} \tag{6}$$

where $O(P^{(i)})$ is the estimate fall risk for the i^{th} person in the test group, $O^{(i)}$ is the real fall risk for that person and m is the total number of people in the test group.

Number of clusters is one of the important factors, which plays vital role in clustering problem (especially when the number of factors in each combination increases). To take this effect into account, four different numbers of clusters have been considered for each combination and the error percentages have been compared.

Results and discussion:

The parameters of table 1 are divided into two different categories, eye open and eye close. First the effect of each of these categories is discussed separately and then both categories are considered together.

As the first part, the effectiveness of sample entropy in x and y direction in opened eye mode in fall risk assessment is investigated.

To simplify the problem, a new notation is introduced as follows. According to this notation each combination is represented with a $1 \times m$ matrix, which m is the number of discussed factor. A number has been assigned to each parameter, which also shows the column number for that parameter in the combination matrix. If the i^{th} component of combination matrix was one, it means that the i^{th} factor is in the combination and if it was zero, the factor is not in that combination. For example, $\begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix}$ states that only the first and last factors are in this combination. Table 2 shows the discussed factors and assigned numbers to each of them

Table 2 – discussed factors and their associated numbers

Factor Name	assigned Number
sample entropy_force plate_ center of pressure_eye open_X1	1
sample entropy_force plate_ center of pressure_ eye open _Y1	2
sample entropy_force plate_ center of pressure_ eye open _X2	3
sample entropy_force plate_ center of pressure_ eye open _Y2	4

Different combination of factors and real and estimated fall risk probability for the test group has been summarized in table 3.

Table 3 - different factor combinations and estimated fall risk

Test data No. / combination	Real fall risk	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]	[1 1 0 0]	[1 0 1 0]	[1 0 0 1]	[0 1 1 0]	[0 1 0 1]	[0 0 1 1]	[1 1 1 0]	[1 1 0 1]	[1 0 1 1]	[0 1 1 1]	[1 1 1 1]
1	0.2	0.18	0.44	0.51	0.54	0.21	0.19	0.19	0.39	0.38	0.44	0.24	0.32	0.26	0.39	0.4
2	0.6	0.45	0.46	0.52	0.55	0.55	0.54	0.55	0.49	0.49	0.55	0.56	0.56	0.56	0.49	0.56
3	0.4	0.26	0.1	0.52	0.54	0.11	0.3	0.26	0.11	0.14	0.44	0.11	0.15	0.29	0.14	0.15
4	0	0.5	0.44	0.47	0.08	0.45	0.48	0.1	0.36	0.08	0.09	0.41	0.1	0.09	0.08	0.1
5	0	0.49	0.44	0.05	0.07	0.44	0.08	0.07	0.12	0.08	0.13	0.1	0.09	0.13	0.12	0.12
6	0.2	0.09	0.55	0.06	0.39	0.18	0.1	0.15	0.11	0.41	0.09	0.11	0.13	0.09	0.11	0.11
7	0	0.42	0.06	0.5	0.37	0.44	0.52	0.53	0.09	0.08	0.37	0.51	0.5	0.55	0.09	0.49
8	0	0.43	0.44	0.52	0.48	0.44	0.49	0.47	0.38	0.35	0.51	0.31	0.33	0.47	0.36	0.34
9	0	0.5	0.16	0.48	0.49	0.24	0.37	0.46	0.2	0.15	0.33	0.28	0.17	0.29	0.19	0.21
10	0	0.05	0.52	0.51	0.35	0.12	0.06	0.11	0.57	0.39	0.37	0.14	0.1	0.08	0.38	0.11
11	0	0.06	0.38	0.49	0.48	0.21	0.06	0.12	0.33	0.33	0.48	0.22	0.13	0.09	0.33	0.14
12	0	0.6	0.45	0.47	0.54	0.54	0.35	0.62	0.41	0.47	0.33	0.46	0.55	0.36	0.37	0.46
13	0.2	0.55	0.05	0.45	0.46	0.06	0.31	0.48	0.09	0.07	0.35	0.08	0.08	0.3	0.08	0.08
14	0	0.2	0.54	0.51	0.55	0.22	0.26	0.21	0.49	0.48	0.43	0.22	0.25	0.21	0.44	0.26
15	0	0.59	0.13	0.52	0.51	0.14	0.53	0.59	0.14	0.18	0.47	0.14	0.18	0.5	0.18	0.18

Figure 1 shows the RMSE for different combination of effective factors. It is observed that when the number of factors increases, the RMSE error generally decreases. The minimum RMSE error is 24%, which belongs to the case that all the four factors have been considered and the maximum RMSE percentage is 40%, for the case that just fourth factor had been considered.

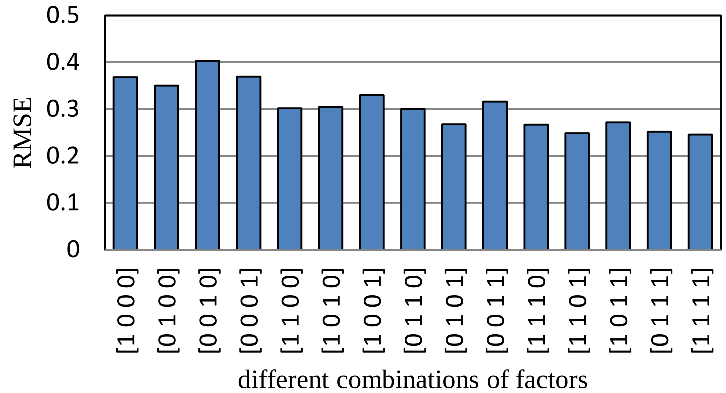

Fig 1- Root mean square error for different combination of eye open factors

The number of clusters is an important factor in designing a fuzzy clustering system. All the data points that are put in the same cluster are subjected to the same fuzzy rules. Therefore, reducing the number of clusters reduces the ability of the system to distinguish the difference between data points. On the other hand, increasing the number of cluster makes the system more complex and it can fit better to the input output map. Considering too many clusters, however, eliminates the disturbance rejection ability of the system, which is the main advantage of this method, and may lead to more random predictions.

In all of the above cases, the number of clusters was 5, to investigate the effect of number of clusters on the accuracy of introduced algorithm; the algorithm has been repeated with number of clusters equal to 4, 6, 7 and 8. Figure 2 shows the RMSE for different number of clusters.

It is observed that for different number of clusters, the outputs of the trained system are approximately close to each other, just as much as the number of clusters increases, the randomness of the output of the algorithm increases. Therefore, we can find the minimum number of clusters that can acceptably approximate the input-output mapping in a repeatable manner.

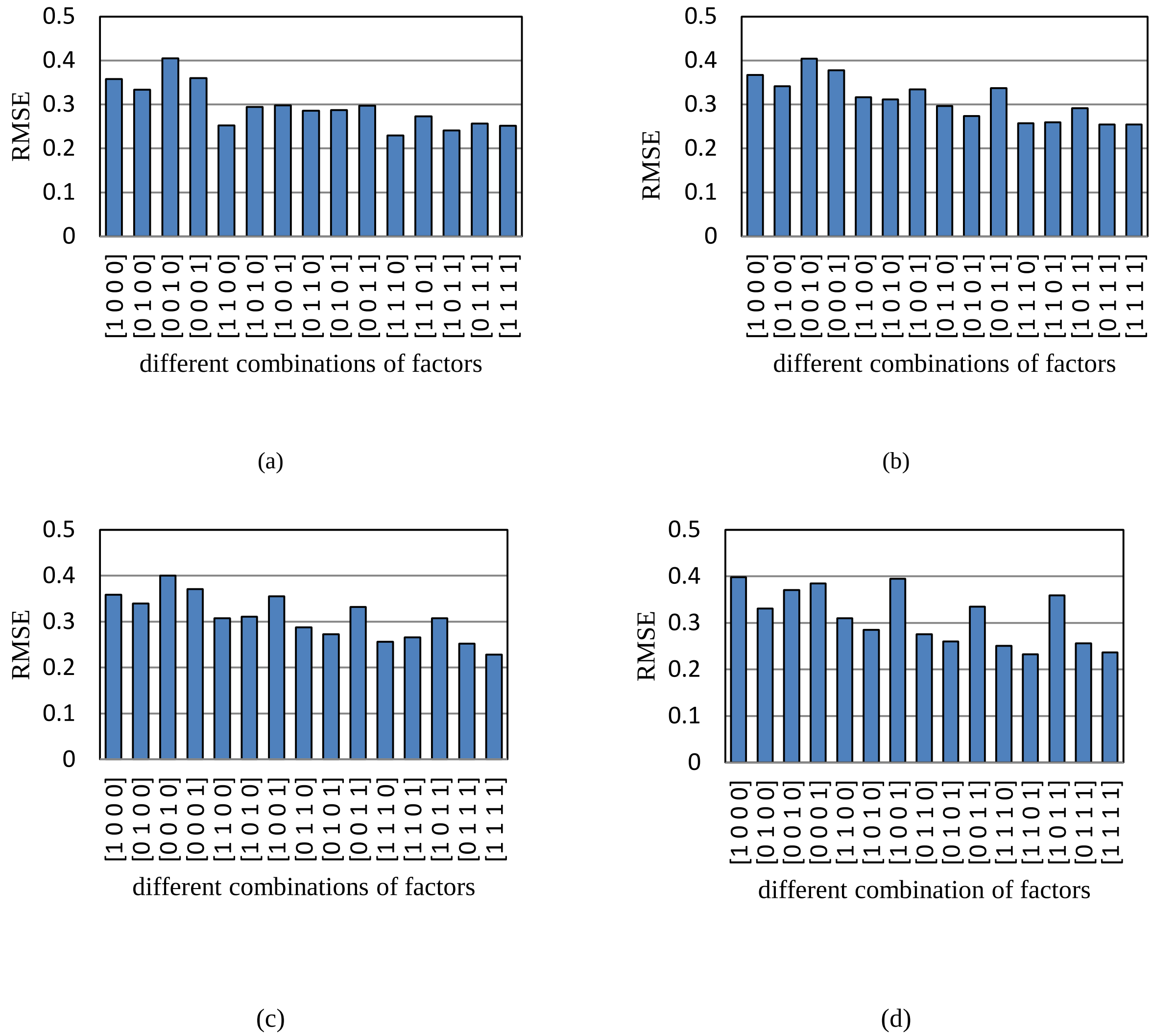

Fig 2- RMSE for different number of clusters: a) 4 clusters b) 6 clusters c) 7 clusters d) 8 clusters

After opened eyes mode, the procedure is repeated for closed eyes data. Again a number has been assigned to each of the closed eyes factors. Table 4 shows the closed eyes factors and the assigned numbers.

Table 4 – closed eyes parameters and assigned numbers to each factors

Factor Name	Assigned Number
sample entropy_force plate_ center of pressure_eye close_X1	1
sample entropy_force plate_ center of pressure_ eye close_Y1	2
sample entropy_force plate_ center of pressure_ eye close_X2	3
sample entropy_force plate_ center of pressure_ eye close_Y2	4

The proposed algorithm has been applied on eye close mode factors with the number of clusters equal to five. Again Different combination of effective factors and real and estimated fall risk probability for the test group has been considered, the results have been summarized in Table 5.

Table 5- different factor combination and estimated fall risk

Test data No. / combination	Real fall risk	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]	[1 1 0 0]	[1 0 1 0]	[1 0 0 1]	[0 1 1 0]	[0 1 0 1]	[0 0 1 1]	[1 1 1 0]	[1 1 0 1]	[1 0 1 1]	[0 1 1 1]	[1 1 1 1]
1	0.2	0.54	0.58	0.06	0.22	0.61	0.11	0.3	0.08	0.29	0.14	0.32	0.32	0.21	0.16	0.43
2	0.6	0.38	0.33	0.05	0.55	0.4	0.08	0.22	0.07	0.39	0.11	0.11	0.23	0.13	0.11	0.13
3	0.4	0.54	0.49	0.4	0.56	0.52	0.26	0.41	0.45	0.54	0.39	0.17	0.34	0.31	0.38	0.33
4	0	0.5	0.04	0.53	0.52	0.05	0.51	0.57	0.05	0.11	0.53	0.06	0.11	0.57	0.11	0.12
5	0	0.52	0.27	0.22	0.23	0.28	0.22	0.37	0.19	0.36	0.29	0.18	0.42	0.43	0.49	0.55
6	0.2	0.46	0.26	0.06	0.56	0.4	0.15	0.32	0.12	0.39	0.21	0.22	0.46	0.25	0.19	0.24
7	0	0.49	0.43	0.53	0.3	0.48	0.48	0.35	0.43	0.33	0.3	0.42	0.36	0.35	0.33	0.37
8	0	0.47	0.04	0.53	0.56	0.05	0.47	0.47	0.05	0.08	0.56	0.06	0.08	0.47	0.08	0.12
9	0	0.51	0.45	0.52	0.48	0.42	0.5	0.45	0.47	0.43	0.43	0.45	0.41	0.42	0.38	0.38
10	0	0.47	0.23	0.51	0.56	0.25	0.45	0.46	0.23	0.18	0.57	0.2	0.22	0.46	0.2	0.25
11	0	0.54	0.46	0.37	0.52	0.49	0.43	0.42	0.35	0.49	0.53	0.52	0.34	0.39	0.53	0.34
12	0	0.38	0.57	0.18	0.55	0.41	0.09	0.17	0.16	0.54	0.27	0.15	0.13	0.17	0.3	0.25
13	0.2	0.46	0.21	0.39	0.06	0.23	0.47	0.07	0.2	0.1	0.12	0.21	0.1	0.12	0.11	0.11
14	0	0.49	0.26	0.46	0.56	0.31	0.49	0.41	0.28	0.24	0.41	0.31	0.28	0.4	0.19	0.23
15	0	0.46	0.58	0.17	0.42	0.5	0.16	0.41	0.14	0.42	0.17	0.11	0.42	0.2	0.23	0.34

Figure 3 show the RMSE for different combination of effective factors in eye close mode.

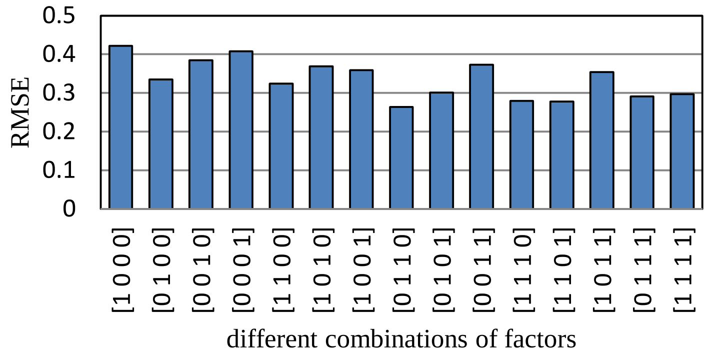

Fig. 3- Root mean square error for different combination of eye open factors

Again, it is observed that the maximum RMSE is for the case that just one factor has been considered and as the number of considered factor increases, RMSE approximately decreases. Like open eye mode, the algorithm has been repeated for different number of clusters and the results have been summarized in Figure 4.

For the closed eyes case, it is also observed that the RMSE values for different number of clusters are close to each other, as it was mentioned in opened eyes mode, the increase in number of clusters leads to more random results. Therefore, an optimum number of clusters can be found by try and error.

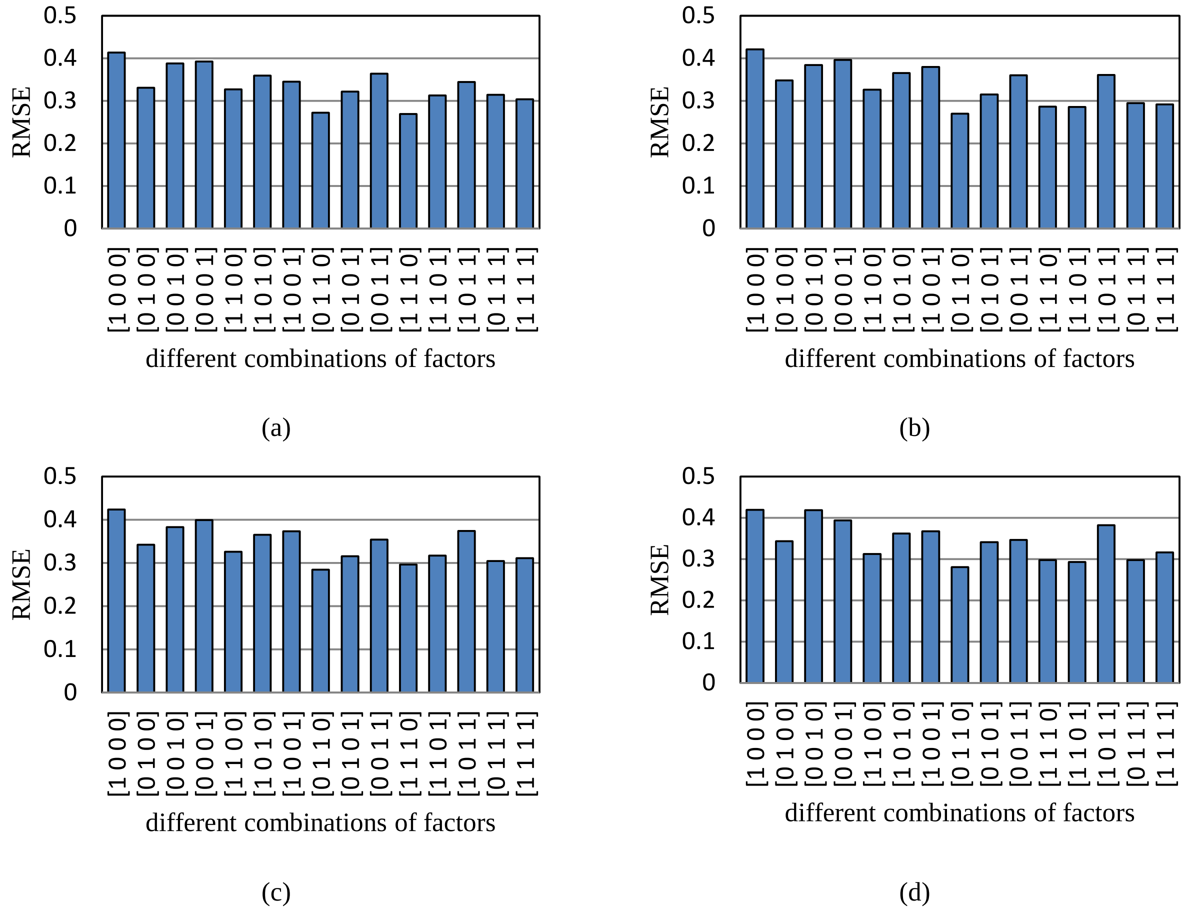

Fig. 4- RMSE for different number of clusters: a) 4 clusters b) 6 clusters c) 7 clusters d) 8 clusters

Finally both cases of opened eyes and closed eyes are investigated together and different combinations of all factors are discussed. Table 6 shows discussed factors and the numbers which are assigned to these factors for simplification as well.

Table 6 – eye open and eye close factors and the associated numbers

Factor Name	Associated Number
sample entropy_force plate_ center of pressure_eye open_X1	1
sample entropy_force plate_ center of pressure_ eye open _Y1	2
sample entropy_force plate_ center of pressure_ eye open _X2	3
sample entropy_force plate_ center of pressure_ eye open _Y2	4
sample entropy_force plate_ center of pressure_eye close_X1	5
sample entropy_force plate_ center of pressure_eye close_Y1	6
sample entropy_force plate_ center of pressure_eye close_X2	7
sample entropy_force plate_ center of pressure_eye close_Y2	8

RMSE for different combination of whole 8 factors and 8 clusters has been shown in figure 5, the total number of combinations would be 255, it starts with single factors and would follow up with combination of 2 , 3, up to whole 8 factors respectively.

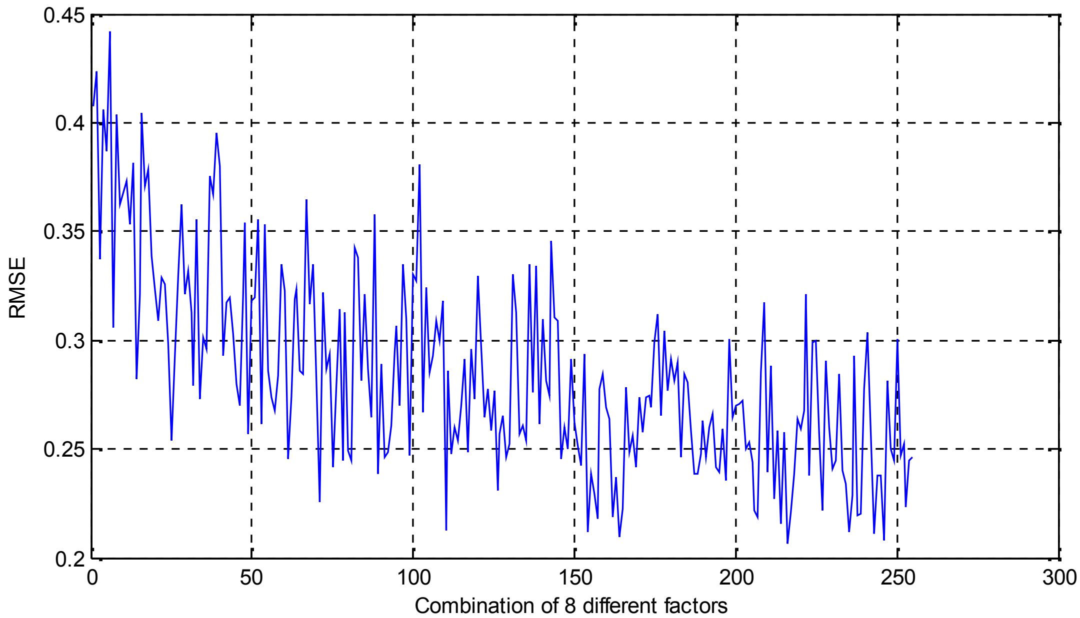

Fig. 5- RMSE for combination of different factors

It is observed that when the number of considered factors increases, the root mean square error decreases approximately, which shows that the accuracy of proposed algorithm increases as more factors are considered. Also the maximum RMSE error is 42.19%, which is for the case that we just consider 5^{th} factor.

As the number of parameters increases, number of clusters may play more important role in the accuracy of this method, because 5 clusters might not be enough for all the factors, Figure 6 shows the RMSE error for different number of clusters.

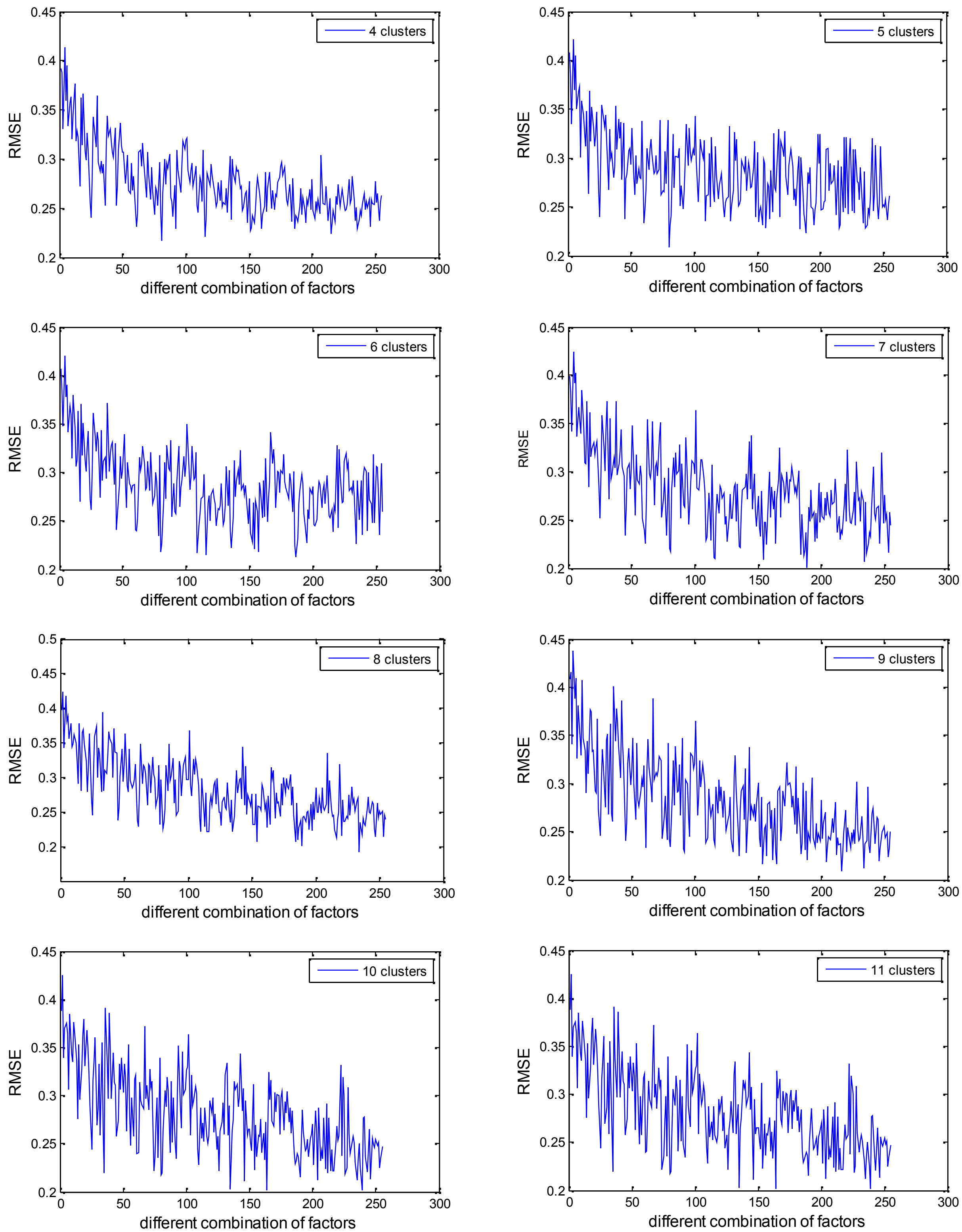

Fig. 6- RMSE for different number of clusters and different combinations of effective factors

It is observed that for the case the 8 numbers of clusters have been considered, the RMSE has smaller values in compare with other cluster numbers. As the number of clusters exceeds above 9, more randomness is observed in the results. It can be conclude that for this number of factors, 8 clusters would be the best. Moreover, as it can be seen in all the cases with different cluster numbers, the rate of error reduction decreases as the number of considered factors increased. It shows that the effects of the newly added factors already exist in the previously considered factors. It cannot be reduced anymore unless new factors are considered which are in a sense more independently affect falling with respect to considered parameters.

Conclusions:

The time series of location of the center of pressure is measured for a group of 101 people between 56 to 90 years old standing on a force plate with open eyes and closed eyes. The sample entropies of these time series are calculated using two different embedding dimensions for each person. These factors are used to design a fuzzy clustering system to predict fall. First all the possible combinations of factors associated with the opened eye tests have been considered. Then, the same analysis has been done for the closed eyes cases. The optimal number of clusters was determined to be 5 via trial and error. It is observed that the maximum errors are related to the cases that only a single factor is considered as an effective factor in fall risk assessment. The more factors were taken into account, the less root mean square errors were reported.

Finally, all the eight entropies are considered as fall risk assessment factors which lead to a more complex system. Therefore, the optimal number of clusters was found to be 8 in these cases. Again, the root mean square error decreases by increasing the number of considered factors. Moreover, the rate of error reduction decreases as the number of considered factors increased. It shows that the effects of the newly added factors already exist in the previously considered factors.

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