Multi-prototype Fuzzy Clustering with Fuzzy K-Nearest Neighbor for Off-line Human Action Recognition

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***Abstract*—Fall detection of elderly in home environment is an important research area. The fall detection is a part of the human action recognition. In this paper, a human action detection using the fuzzy clustering algorithm with the fuzzy K-nearest neighbor from view-invariant human motion analysis is implemented. In particular, the Hu moment invariant features are computed. Then principal component analysis is utilized to select the principal components. The fuzzy clustering algorithm (either fuzzy C-means, Gustafson and Kessel, or Gath and Geva) is implemented on each class to select the prototypes representing the class. From the results, we found that the best classification rate on the validation set is around 99.33% to 100%, and the classification rate on the blind test data set is around 90%. We also compare the result from fuzzy K-nearest neighbor with that from K-nearest neighbor. The fuzzy K-nearest neighbor result is better as expected.**

Keywords—Fall detection; Hu moment invariants; Fuzzy C-means; Gustafson and Kessel clustering; Gath and Geva clustering; Fuzzy K-nearest neighbor

I. INTRODUCTION

Human action recognition is one of the processes that are needed in view-invariant human motion analysis [1, 2]. One of the important application areas for this motion analysis is to detect the fall of elderly in home environment. There are more than 50% of injury-related hospitalizations in people aged over 65. Consequently, some of injury deaths (almost 40%) are from falls [3]. Even though there are several works in view-invariant human motion analysis [4–30], none of them focus on fall detection. There are some research works involving view-invariant fall detection system [31–36], however, the accuracy of these systems is approximately 90–97%. Although, there are some other related works with approximately 100%, those systems either use several cameras [37–47] or the accuracy reported is based on only one subject [48] or the detection systems are built based on 2-class detection that might not be appropriate for daily live [50].

In this paper, we use a fuzzy clustering and fuzzy K-nearest neighbor to detect human action with the data set from [33]. In particular, we utilize features extracted from the Hu moment invariants and then the principal component analysis is computed. Then a fuzzy clustering algorithm (Fuzzy C-Means, Gustafson and Kessel Clustering, or Gath and Geva Clustering) is used to create multi-prototypes for each action. Finally, the fuzzy K nearest neighbor is utilized to detect human action.

II. BACKGROUND THEORIES

A. Hu Moment Invariants

The Hu moment invariants [50, 51] is now briefly described. For a 2-dimensional binary image, $(p+q)^{th}$ order geometrical moments m_{pq} is

$$m_{pq} = \sum_y \sum_x x^p y^q f(x,y)\ ,\ \ p,q = 0,1,2,\ldots, \tag{1}$$

where $f(x,y)$ is either 0 or 1 value at coordinate (x,y). Then the central moments (μ_{pq}) are computed by

$$\mu_{pq} = \sum_y \sum_x (x-\bar{x})^p (y-\bar{y})^q f(x,y), \tag{2}$$

where $\bar{x} = \frac{m_{10}}{m_{00}}$ and $\bar{y} = \frac{m_{01}}{m_{00}}$. Since the object center is shifted to the center of image, μ_{pq} is translation invariant. The normalized central moments are defined as follow:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^r},\ \ \text{for}\ p+q = 2,3,\ldots, \tag{3}$$

where $r = \frac{p+q}{2} + 1$. Then the extracted features are

$$\varphi_1 = \eta_{20} + \eta_{02} \tag{4}$$

$$\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{5}$$

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{6}$$

$$\varphi_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{7}$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (8)$$

$$\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (9)$$

$$\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] . \quad (10)$$

Since these features are non-orthogonal, i.e., their basis functions are correlated, we use the principal component analysis to solve this problem.

B. *Principal Component Analysis (PCA)*

Now, we briefly describe the principal component analysis (PCA) [52]. Suppose $\mathbf{X} \in \Re^{n \times p}$ contains n samples with p dimensions. The covariance matrix Σ is

$$\Sigma = \mathbf{V}\Lambda\mathbf{V}^t , \quad (11)$$

where $\mathbf{V}$ is an orthogonal matrix with eigenvectors as its column vectors. Λ is a diagonal matrix with eigenvalues sorted in decreasing order ($\lambda_1 \le \lambda_2 \le \ldots \le \lambda_p$) as its diagonal elements. The transformation matrix $\mathbf{P} \in \Re^{p \times a}$ is used to select a eigenvectors (principal components (PCs)). The cumulative percent variance (CPV) [36, 37] is used to measure the percent variance captures by the first a PCs. The CPV is calculated as

$$\text{CPV}(a) = \frac{\sum_{k=1}^{a} \lambda_k}{trace(\Lambda)} \times 100, \quad \text{for } a \le p . \quad (12)$$

Then the uncorrelated data set $\mathbf{Y}$ is

$$\mathbf{Y} = \mathbf{XP}. \quad (13)$$

This data set is used in the clustering.

C. *Fuzzy Clustering Algorithm*

In this paper, we use the fuzzy C-means clustering, Gustafson and Kessel clustering and Gath and Geva clustering. We first briefly review the Fuzzy C-means (FCM) algorithm [53, 54] here. Let X = $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$ be a set of vectors, where each vector is a p-dimensional vector. The update equation for FCM is as follows [54]

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left[\frac{\left\| \mathbf{x}_i - \mathbf{c}_j \right\|}{\left\| \mathbf{x}_i - \mathbf{c}_k \right\|} \right]^{\frac{2}{m-1}}} , \quad (14)$$

$$\mathbf{c}_j = \frac{\sum_{i=1}^{N} u_{ij}^m \mathbf{x}_i}{\sum_{i=1}^{N} u_{ij}^m} , \quad (15)$$

where, u_{ij} is the membership value of vector $\mathbf{x}_j$ belonging to cluster j, $\mathbf{c}_j$, is the center of cluster j, and m is the fuzzifier. The following is the summarization of the FCM algorithm.

Fix the number of clusters C
Initiate prototypes
Do {
Update membership using (14)
Update prototypes using (15)
} Until prototypes stabilize

Now, we briefly explain the Gustafson and Kessel clustering (GK) [55, 56]. The center and membership update equations are similar to equations (14) and (15), but the distance is computed as

$$d^2\left(\mathbf{x}_j, \mathbf{c}_i\right) = \left|\Sigma_i\right|^{\frac{1}{p}} \left(\mathbf{x}_j - \mathbf{c}_i\right)^t \Sigma_i^{-1} \left(\mathbf{x}_j - \mathbf{c}_i\right), \quad (16)$$

where
$$\Sigma_i = \frac{\sum_{j=1}^{n} u_{ji}^m \left(\mathbf{x}_j - \mathbf{c}_i\right)^t \left(\mathbf{x}_j - \mathbf{c}_i\right)}{\sum_{j=1}^{n} u_{ji}^m} . \quad (17)$$

However, for some data sets, the covariance matrix might be singular. Hence, the covariance is updated as [57]

$$\Sigma_i = (1-\gamma)\Sigma_i + \gamma\left|\Sigma_0\right|^{\frac{1}{P}} \mathbf{I} , \quad (18)$$

where Σ_0 is a covariance matrix of the whole data set. Then eigenvectors and eigenvalues are computed from Σ_i. Suppose $\lambda_{ik}^{\max} = \max(\lambda_{ik})$, for $k = 1, 2, \ldots, p$, set

$$\lambda_{ik}^{new} = \frac{\lambda_{ik}^{\max}}{\beta} , \ \forall_k \text{ for which } \frac{\lambda_{ik}^{\max}}{\lambda_{ik}} > \beta . \quad (19)$$

Finally, Σ_i is recomputed using

$$\Sigma = \mathbf{V}\Lambda^{new}\mathbf{V}^t . \quad (20)$$

In our experiment, we set γ = 0.5 and β = 10^{15}. The GK algorithm is similar to that of the FCM.

Again, for the Gath and Geva clustering (GG) [58], the center and membership update equations are similar to equations (14) and (15). The distance is computed as

$$d^2\left(\mathbf{x}_j, \mathbf{c}_i\right) = \frac{\left|\Sigma_i\right|^{\frac{1}{2}}}{P_i} \exp\left(\frac{\left(\mathbf{x}_j - \mathbf{c}_i\right)^t \Sigma_i^{-1} \left(\mathbf{x}_j - \mathbf{c}_i\right)}{2} \right), \quad (21)$$

where P_i is *a priori* probability of cluster i. Again, the covariance matrix might be singular, we use the same strategy as in equations (17) to (20). We also set γ = 0.5 and β = 10^{15}. The GG algorithm is similar to the FCM algorithm. For all three algorithms we set m = 2.

D. Fuzzy K-Nearest Neighbor

After, we create multi-prototypes, i.e., $\mathbf{C}=\left\{\mathbf{c}_1^1,\ldots\mathbf{c}_{N_1}^1,\mathbf{c}_1^2,\ldots\mathbf{c}_{N_2}^2,\ldots,\mathbf{c}_1^C,\ldots\mathbf{c}_{N_C}^C,\right\}$ where $\mathbf{c}_k^j$ is prototype k in class j and N_j is the number of prototypes in class j, for each action class. We implement the fuzzy K-nearest neighbor [59]. In the algorithm, after the K nearest neighbors are found for vector **x**, the membership value of **x** in class i is computed as

$$u_i(\mathbf{x})=\frac{\sum_{j=1}^{K}u_{ij}\left(1\Big/\left\|\mathbf{x}-\mathbf{c}_j^q\right\|\right)^{2/m-1}}{\sum_{j=1}^{K}\left(1\Big/\left\|\mathbf{x}-\mathbf{c}_j^q\right\|\right)^{2/m-1}}, \tag{22}$$

where u_{ij} is the membership value of prototype $\mathbf{c}_j^q$ in class i. Then, the decision is as follow:

x is assigned to class i if $u_i(\mathbf{x}) > u_j(\mathbf{x})$ for $j\neq i$.

In our experiment, since we know that the prototype represents which class, we set u_{jq} = 1 for $\mathbf{c}_j^q$ in class q and 0 for all the other classes. Also, we set m = 1.5 in our experiment.

III. EXPERIMENTAL RESULTS

The data set used in this paper is from [33, 60]. The data set consists of several video contents recorded from 4 subjects who perform 4 actions, i.e., standing or walking, sitting or bending, lying and lying forward. Since lying and lying forward are considered as an action of falling, we collapse both actions into one action. We extract several frames from videos and segment the region of interest manually. Then pixels in the region of interest (called silhouette) are set to 1 and the rest is set to 0. Example of the selected frames and their corresponding silhouette images are shown in figure 1. Hence, there are three classes in our experiment, i.e., stand, sit, and lying, each class with 510 manually selected frames. Therefore there are 1530 frames in total. We randomly select 500 frames from each class (1500 frames in total) to be our training data set and the rest 30 frames to be our blind test data set. We implement 10-fold cross validation on the training data set.

The seven features in equations (4) to (10) are computed from manually created silhouette image in each frame. Then, the PCA is implemented with 3PCs and 7PCs selected. The 3PCs is selected based on the CPV ≥ 85% whereas 7PCs is chosen based on CPV ≥ 100%. This work is actually inspired by the work of Banerjee *et al.* [61, 62]. They tried to find the sitting and standing frame using fuzzy clustering algorithm. Here, we implement each fuzzy clustering algorithm with 40, 45, 50, 55, and 60 clusters on each class separately to create multi-prototypes for each class. Because PCA features are overlapped between classes and they are spreading within class as shown in figure 2. The multi-prototype algorithm is chosen to capture a small cluster and cover all the feature vectors in each class.

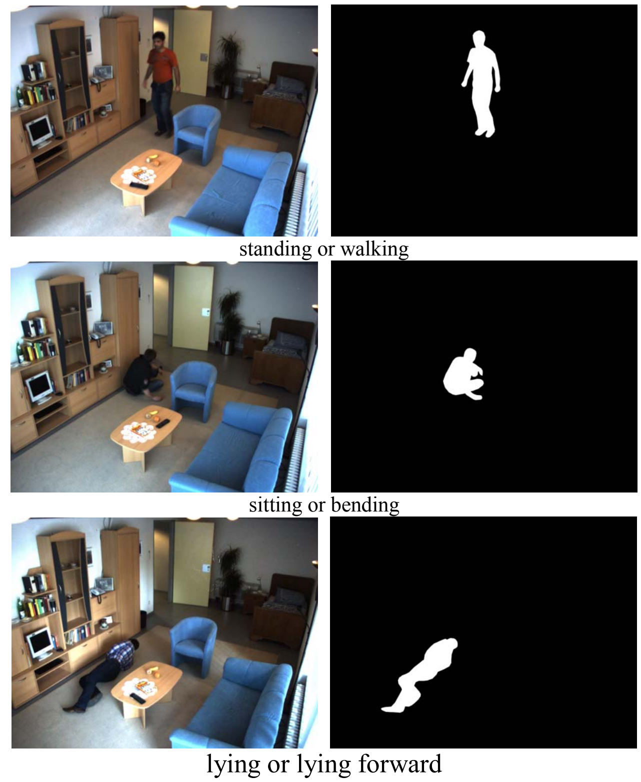

Fig. 1. Examples of selected frames and their corresponding silhouette images

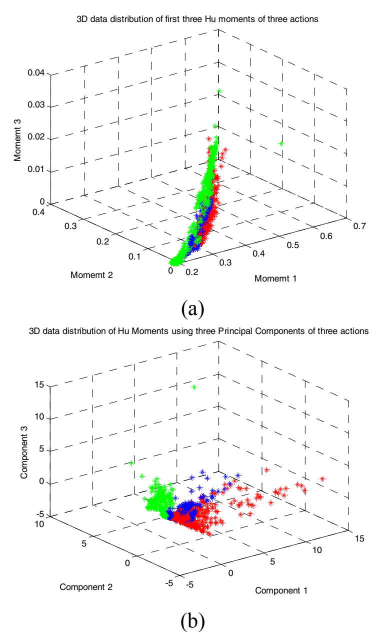

Fig. 2. (a) First 3 moments and (b) 3 features from PCA (red is for stand, green is for sit and blue is for lying)

Then the FKNN with K = 1, 3, 5, and 7 is implemented as a classifier on each set of created multi-prototypes. Tables 1 to 4 show the best and the average correct classification on the validation set for 1, 3, 5, and 7 FKNN, respectively. It can be seen that the best classification (100%) on the validation set is from the GG with 60 clusters on 3PCs with 5 FKNN (called GG1) and from the GK with 50 clusters on 7 PCs with 1 FKNN (called GK1). The next highest correct classification (99.33%) is from the FCM with 60 clusters on 7PCs with 7 FKNN (called FCM1) and from the GK with 50 clusters on 7 PCs with 7 FKNN (called GK2) as well. We use the set from the four best results on the validation set with the blind test data set shown in tables 5 to 8. The correct classification rates of the blind test data set from the GG1 and GK1 are 80% and 86.67%, respectively, whereas those from the FCM1 and GK2 are 90%. As we expect, the GG1 and GK1 might be overtrained somehow. From [32], they report that the correct classification on the training data set is around 98.06%. Although, we cannot directly compare the result, our result is still comparable with that.

For one's curiosity, we also implement this multi-prototype setting with the regular K-nearest neighbor (KNN) with 1, 3, 5, and 7. However, 1 FKNN is actually 1KNN because of the method we set the membership u_{ij} in equation (22). Therefore, the GK1 is also the best in the validation set but gives 86.67% on the blind test data set. Hence, the next best algorithm is from the GG with 40 clusters on 7 PCs with 3 KNN (called GG2) and from the GK with 55 clusters on 7 PCs with 3 KNN (called GK3). Tables 9 and 10 show the confusion matrices from GG2 and GK3 on the blind test data set, respectively. The GG2 and GK3 yield 83.33% and 86.67% correct classification rates on blind test data set, respectively. As we expect, the FKNN performs better than the KNN.

TABLE I. CORRECT CLASSIFICATION ON VALIDATION SET USING FKNN WITH 1 NN

#PCs	# of prototypes in each class	FCM		GK		GG	
		Avg.	Best	Avg.	Best	Avg.	Best
3	40	93.13	97.33	93.67	96.00	93.73	96.00
	45	93.20	96.00	93.40	96.00	93.40	96.67
	50	94.00	95.33	93.80	96.00	93.67	96.67
	55	93.80	96.67	94.20	96.67	93.67	96.00
	60	94.40	96.00	94.07	98.00	94.13	97.33
7	40	95.33	98.00	95.47	98.00	95.40	97.33
	45	95.20	98.67	95.80	97.33	95.47	96.67
	50	95.87	96.67	95.87	100.00	95.67	98.67
	55	95.93	97.33	95.87	98.00	95.93	99.33
	60	95.93	98.67	96.00	97.33	96.20	99.33

TABLE II. CORRECT CLASSIFICATION ON VALIDATION SET USING FKNN WITH 3 NN

#PCs	# of prototypes in each class	FCM		GK		GG	
		Avg.	Best	Avg.	Best	Avg.	Best
3	40	93.33	95.33	93.53	96.00	93.47	96.00
	45	93.27	96.67	93.80	96.00	93.73	96.00
	50	93.73	96.67	94.07	97.33	93.87	95.33
	55	93.87	97.33	94.40	97.33	93.87	98.00
	60	94.44	96.00	94.33	96.67	94.53	98.00
7	40	95.53	98.00	95.93	98.00	96.13	97.33
	45	95.53	98.00	95.73	98.00	95.80	97.33
	50	96.27	98.00	96.27	98.67	95.93	98.00
	55	96.20	97.33	96.27	98.67	96.27	98.00
	60	95.93	98.00	96.33	98.00	96.67	99.33

TABLE III. CORRECT CLASSIFICATION ON VALIDATION SET USING FKNN WITH 5 NN

#PCs	# of prototypes in each class	FCM		GK		GG	
		Avg.	Best	Avg.	Best	Avg.	Best
3	40	93.33	95.33	93.60	96.00	93.67	97.33
	45	93.27	96.67	93.67	96.67	93.67	99.33
	50	93.53	96.00	94.07	96.00	93.67	98.67
	55	94.00	97.33	94.27	97.33	93.87	98.00
	60	94.80	96.67	94.27	98.00	94.33	100.00
7	40	95.47	98.00	95.80	98.67	95.93	96.00
	45	95.53	98.67	95.93	98.67	96.00	97.33
	50	96.13	98.00	96.40	98.67	96.07	96.67
	55	96.13	98.00	96.40	98.67	96.47	96.00
	60	96.00	98.00	96.40	98.00	96.60	98.00

TABLE IV. CORRECT CLASSIFICATION ON VALIDATION SET USING FKNN WITH 7 NN

#PCs	# of prototypes in each class	FCM		GK		GG	
		Avg.	Best	Avg.	Best	Avg.	Best
3	40	93.13	95.33	93.53	96.00	93.53	96.00
	45	93.07	96.00	93.80	96.67	93.47	97.33
	50	93.60	96.00	93.93	97.33	93.60	95.33
	55	93.93	96.67	94.20	96.67	93.87	96.00
	60	94.27	96.00	94.20	97.33	93.93	98.00
7	40	95.47	98.67	95.73	98.67	95.73	97.33
	45	95.40	98.00	95.93	98.00	95.87	97.33
	50	96.07	98.00	96.20	99.33	95.80	99.33
	55	96.13	97.33	96.33	98.67	96.53	98.67
	60	96.00	99.33	96.27	98.67	96.60	98.67

TABLE V. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM GG WITH 60 CLUSTERS ON 3PCS WITH 5 FKNN →80%

Actual action	Algorithm's output		
	Stand(including walk)	Sit(including bend)	Lying
Stand (including walk)	9	0	1
Sit (including bend)	0	10	0
Lying	5	0	5

TABLE VI. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM GK WITH 50 CLUSTERS ON 7PCS WITH 1 FKNN→86.67%

Actual action	Algorithm's output		
	Stand (including walk)	Sit (including bend)	Lying
Stand (including walk)	10	0	0
Sit (including bend)	0	10	0
Lying	4	0	6

TABLE VII. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM FCM WITH 60 CLUSTERS ON 7PCS WITH 7 FKNN→90%

Actual action	Algorithm's output		
	Stand (including walk)	Sit (including bend)	Lying
Stand (including walk)	10	0	0
Sit (including bend)	0	9	1
Lying	2	0	8

TABLE VIII. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM GK WITH 50 CLUSTERS ON 7PCS WITH 7 FKNN →90%

Actual action	Algorithm's output		
	Stand (including walk)	Sit (including bend)	Lying
Stand (including walk)	10	0	0
Sit (including bend)	0	10	0
Lying	3	0	7

TABLE IX. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM GG WITH 40 CLUSTERS ON 7PCS WITH 3 KNN →83.33%

Actual action	Algorithm's output		
	Stand (including walk)	Sit (including bend)	Lying
Stand (including walk)	10	0	0
Sit (including bend)	0	10	0
Lying	5	0	5

TABLE X. CONFUSION MATRIX OF THE BLIND TEST DATA SET FROM GK WITH 55 CLUSTERS ON 7PCS WITH 3 KNN →86.67%

Actual action	Algorithm's output		
	Stand (including walk)	Sit (including bend)	Lying
Stand (including walk)	10	0	0
Sit (including bend)	0	10	0
Lying	6	0	4

IV. CONCLUSION

In this paper, we implement a human detection system using the fuzzy clustering algorithm with the fuzzy K-nearest neighbor. In particular, the seven features (φ_1 - φ_7) of the Hu moment invariants are computed. Then principal component analysis is utilized to select the principal components. The fuzzy clustering algorithm (either the fuzzy C-means (FCM), Gustafson and Kessel (GK), or Gath and Geva (GG)) is implemented on each class to select prototypes representing the class. Finally, the fuzzy K-nearest neighbor (FKNN) is utilized as a classifier. From the result, we found that the GG with 60 clusters on 3PCs with 5 FKNN and the GK with 50 clusters on 7 PCs with 1 FKNN produce 100% correct classification on the validation set. But, they yield 80% and 86.67% on the blind test data set. This might be because of the overtraining. However, the FCM with 60 clusters on 7PCs with 7 FKNN and the GK with 50 clusters on 7 PCs with 7 FKNN give 99.33% correct classification. They also produce 90% correct classification on the blind test data set. When the K-nearest neighbor is utilized instead of fuzzy K-nearest neighbor, the result is deteriorated.

Although, this system can detect standing or walking, sitting or bending and lying or lying forward in each frame, it is not a complete human action detection system. We are expecting to embed this system into our fully automated system in the future work.

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