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# Sit-to-Stand Detection using Fuzzy Clustering Techniques

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***Abstract*—The ability to rise from a chair is an important parameter to assess the balance deficits of a person. In particular, this can be an indication of risk for falling in elderly persons. Our goal is automated assessment of fall risk using video data. Towards this goal, we present a simple yet effective method of detecting transition, i.e. sit-to-stand and stand-to-sit, from image frames using fuzzy clustering methods on image moments. The technique described in this paper is shown to be robust even in the presence of noise and has been tested on several data sequences using different subjects yielding promising results.**

## I. Introduction

FALL risk assessment has been a goal of our research [1] as we continue to conduct experiments at Tiger Place, an "aging in place" facility for the elderly. An important parameter of the physical functionality analysis is the sit-to-stand measurements such as the time to rise from a chair and the motion of the torso while getting up from a chair. As a part of a continuous assessment system, it is important to be able to segment out the activities of the subject being monitored with a special emphasis on identifying the transitions of sit-to-stand and stand-to-sit.

Background subtraction techniques using Mixture of Gaussian models with texture features are used on the raw image data to separate the foreground from the background, and the resulting silhouettes are then taken as input to the automatic activity segmentation system. Since our goal is to build an automated video surveillance system to continuously monitor elderly persons as they perform their day-to-day activities, we maintain their privacy by using silhouettes instead of raw images for further analysis. It has been shown previously that silhouettes address the privacy concerns of elderly persons participating in our studies and increase their willingness to accept video monitoring systems in their households [14]. From these silhouettes, image moments are extracted, which are then clustered to produce fuzzy labels in the two basic categories.

Clustering is in itself a very fuzzy concept [2]. Depending on the clustering algorithm implemented, the criterion function to be optimized changes, and the nature and shape of the clusters vary. Hence, a key concept in clustering, fuzzy or otherwise, is that no clustering result is right or wrong. Depending on the data set, there can be several possible results, each of which is correct. This issue will be revisited later in this paper.

Oikonomopoulos et al. [3] used visual operators based on optical flow techniques and B splines for activity recognition of running, jumping, walking and other activities. However, the final classifier used was the Relevance Vector Machine which is supervised in nature, thus requiring labeled training data. In another approach for activity segmentation, Stauffer et al. [4] proposed clustering the RGB values of pixels to detect background changes, but the activities were identified using a huge data base with prototypes of all the activities which essentially made the segmentation more supervised in nature.

The sit-to-stand activity was analyzed by Allin et al. [5] using 2D and 3D image descriptors from silhouettes and centroid locations from 3 different camera views. They computed features such as distance of the torso from the feet, the angle created by the torso, head and feet as well as the raw position of the feet and used a decision tree to identify the activities. The ground truth used was obtained by hand labeling the transition data from the video sequence for the two individuals tested.

Berrada et al. [12] used simple image subtraction techniques to extract the pixels indicating motion and then computed the mean and standard deviation along the horizontal and vertical axes to identify sit, attempt to sit, stand, and walk in a given sequence. Checking for motion in the frames in the last two minutes before the stand frame gave the start frame for the beginning of the sit-to-stand activity.

Another interesting approach was proposed by Goffredo et al. [11] to analyze sit-to-stand by finding the points of flexion in the shoulder, knee and hip region using the Gauss-Laguerre Transform and then tracking these natural markers to obtain the trajectories of these points. Finally, the angles obtained at the points of flexion were compared to analyze the sit-to-stand activity.

While clustering was employed in some of the above mentioned techniques and silhouettes were extracted in others, none of them use the combination to segment activities. We present an unsupervised technique to detect transition frames using simple clustering techniques as will be explained in detail in this paper.

The remainder of this paper is organized as follows.

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Silhouette extraction and a description of the moments used for clustering is presented in Section II. Section III describes the fuzzy clustering techniques used for activity analysis, and Section IV describes the preliminary results for selection of the image moments and number of clusters used to initialize the algorithm. The experiments conducted and their results are described in Section V. Finally, the conclusion and future work are presented in Section VI.

## II. SILHOUETTE EXTRACTION AND IMAGE MOMENTS

Silhouette extraction is a background change detection technique whose accuracy depends on how well the background is modeled. The background subtraction method implemented in our work uses color and texture features and employs shadow removal for greater accuracy. Finally, binary morphological operations are used to fill up holes and remove noise from the extracted silhouettes. The technique is explained in detail in [6].

After obtaining the silhouettes from the image sequence, the next step in the algorithm is extracting image moments as shown in the block diagram in Figure 1. Image moments are applicable in a wide range of applications such as pattern recognition and image encoding. One of the most important and popular set of moments is the set of Hu Moments [7]. These are a set of seven central moments taken around the weighted image center. In particular, the first three Hu Moments are more robust than the other Hu Moments in the presence of noise and were used in this analysis.

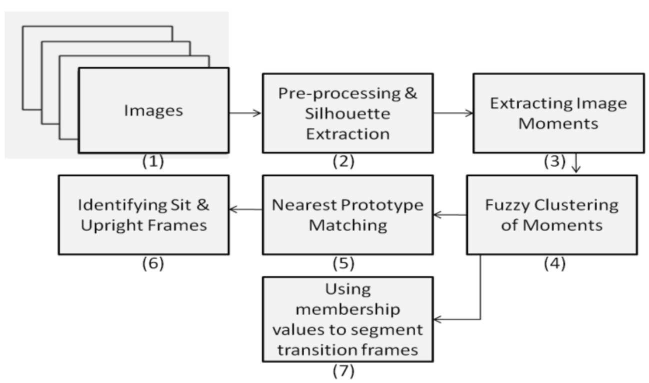


Fig. 1. Block Diagram of Algorithm

In the Hu Moments, the central moments are defined as

$$\mu_{pq} = \sum_{x=1}^{M} \sum_{y=1}^{N} (x-\bar{x})^p * (y-\bar{y})^q * f(x,y), \qquad (1)$$

centered on the image centroid $(\bar{x},\bar{y})$ with f(x,y) being the image intensity value at coordinate (x,y) for an image of dimensions M by N. Using these moments, another set of moments are created using the following formula

$$\eta_{ij} = \frac{\mu_{ij}}{\mu_{00}^{(1+\frac{i+j}{2})}}, \qquad (2)$$

Finally, the first three Hu Moments are computed with the equations (3) - (5) given as:

$$I_1 = \eta_{20} + \eta_{02}, \qquad (3)$$

$$I_2 = (\eta_{20} - \eta_{02})^2 + (2\eta_{11})^2, \qquad (4)$$

$$I_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2, \qquad (5)$$

These moments are scale and rotation invariant which make them extremely robust and applicable in different scenarios. However, they are non-orthogonal in nature; i.e., their basis functions are correlated, making the information captured redundant. In contrast, the Zernike orthogonal moments comprise image moments with higher performance in terms of noise resilience, information redundancy and reconstruction capability.

The Zernike polynomials in polar coordinates [8] are given as:

$$V_{mn}(r,\theta) = R_{mn}(r) * \exp(jn\theta). \qquad (6)$$

The orthogonal radial polynomial is defined by

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}} (-1)^s F(m,n,s,r), \qquad (7)$$

where

$$F(m,n,s,r) = \frac{(m-s)!}{s!\left(\frac{m+|n|}{2}-s\right)!\left(\frac{m-|n|}{2}-s\right)!} r^{m-2s}, \qquad (8)$$

For a discrete image, if $P_{xy}$ is the current pixel intensity (0 or 1 for binary images), the Zernike moments are given by:

$$A_{mn} = \frac{m+1}{\pi} \sum_x \sum_y P_{xy} * V_{mn}(x,y), \qquad (9)$$

Three of the moments were used in this experiment using equation (9) with order, m=2, 3, and 4 and angular dependence, n=0, 1 and 2 respectively. These were selected after implementing Principal Component Analysis to see which moments were most suitable for this application. The clustering algorithms used in the experiments are explained in the next section.

## III. FUZZY CLUSTERING

Fuzzy clustering techniques are used to partition data on the basis of their closeness or similarity using fuzzy methods. As opposed to the hard clustering means, here each element can belong to a certain cluster with varying degrees of membership. In particular, the Gustafson Kessel [16] and Gath and Geva [9] fuzzy clustering techniques were implemented on the image moments described above.

### A. *Gustafson Kessel clustering technique:*

The Gustafson Kessel (GK) Algorithm is an extension of the Fuzzy C Means algorithm in which each cluster has its own unique covariance matrix. This makes the algorithm more robust and more applicable to various data sets which contain ellipsoidal clusters of different orientations and sizes [13]. The basic clustering approach we use is well known and has been summarized here for completeness.

**Algorithm**:

1. Fix c = number of clusters & initialize the iteration counter t=1.
2. Initialize membership matrix U for all the data points and for each of the clusters. (The initialization is explained further in this section.)
3. *Do*
4. Compute the cluster centers using equation (10).

$$\mu_j(t) = \frac{\sum_{i=1}^{N} u_{ij}{}^{q}(t-1) * x_i}{\sum_{i=1}^{N} u_{ij}{}^{q}(t-1)}, \tag{10}$$

5. Compute the covariance matrices for each of the clusters as in equation (11).

$$\Sigma_j(t) = \frac{\sum_{i=1}^{N} u_{ij}{}^{q}(t-1) * (x_i - \mu_j(t)) * (x_i - \mu_j(t))^T}{\sum_{i=1}^{N} u_{ij}{}^{q}(t-1)}, \tag{11}$$

6. Update the partition matrix:

$$u_{ik}(t) = \frac{1}{\sum_{j=1}^{c} (\frac{D_{ik}}{D_{jk}})^{2/(m-1)}}, \tag{12}$$

using the Mahalanobis distance, $D_{ik}$, given by:

$$D_{ik}{}^2 = (x_k - \mu_i(t))^T * \left[ \left| \Sigma_j(t) \right|^{\frac{1}{l}} * \Sigma_j(t)^{-1} \right] * (x_k - \mu_i(t))$$

where $l$ is the length of feature vector $x$.

7. Increment the iteration counter t.
8. *Until* $\| \mu(t) - \mu(t-1) \| < \epsilon$ or t > tmax where $\epsilon$ is the minimum permissible error and tmax is the maximum number of iterations specified.

Here, $\mu$(t) is the vector of all centers and the distance norm employed for determining convergence is the standard Euclidean distance measure. An important point to note is that it is essential to initialize the membership values to random values but with the mean equal to 0.5 and standard deviation equal to one so that the algorithm converges at a much faster rate. Another importance of standardization is the fact that it ensures that equal importance is given to each of the moments used or else the algorithm would weigh on the moments whose range is the highest.

### B. *Gath and Geva:*

This fuzzy clustering technique employs a distance norm based on the fuzzy maximum likelihood estimates [9] as shown below.

**Algorithm:**

1. Fix c = number of clusters.
2. Initialize the membership matrix. (Specified further in the section) Initialize the iteration counter t=1.
3. *Do*
4. Calculate the cluster centers for input x with the membership values *u* as in equation (13)

$$\mu_i(t) = \frac{\sum_{k=1}^{N} u_{ik}^{q} * x_k}{\sum_{k=1}^{N} u_{ik}^{q}}, \tag{13}$$

5. Compute the fuzzy covariance matrix, equation (14).

$$F_i(t) = \frac{\sum_{k=1}^{N} u_{ik}^{q}(t-1) * (x_k - \mu_i(t)) * (x_k - \mu_i(t))^T}{\sum_{k=1}^{N} u_{ik}^{q}(t-1)}, \tag{14}$$

6. The distance between the feature vectors is computed using equation (15).

$$D_{ik}^2 = \frac{2\pi^{\frac{n}{2}} \sqrt{det(F_i(t))}}{\alpha_i} . exp\left(\frac{1}{2}(x_k - \mu_i(t))^T F_i^{-1}(x_k - \mu_i(t))\right) \tag{15}$$

with a priori probability:

$$\alpha_i = \frac{1}{N} \sum_{k=1}^{N} u_{ik}, \tag{16}$$

7. Update the partition matrix:

$$u_{ik}(t) = \frac{1}{\sum_{j=1}^{c} (\frac{D_{ik}}{D_{jk}})^{2/(m-1)}}, \tag{17}$$

8. Increment iteration counter t.
9. *Until* $\| \mu(t) - \mu(t-1) \| < \epsilon$

The distance function is what makes this algorithm so unique. However, due to the exponential distance norm, unless properly initialized, it converges to a near local optimum which could yield erroneous results. Using the simple initialization technique similar to the GK algorithm leads to erroneous results, which is why, for our experiments, the partition matrix is initialized using the resulting partitions of the standard Fuzzy C Means algorithm as suggested in [9].

## IV. PRELIMINARY EXPERIMENTS

A set of preliminary experiments was conducted to establish the input parameters and best features to use for this domain. Seven participants performed different styles of sit-to-stand motions. As described in Section II, silhouettes were extracted from the raw image sequences, and the moments were computed as features. Ground truth was established using a Vicon motion capture system. See also Section V for further details on the experimental setup.

### A. *Determining Number of Clusters*

As described in the previous section, both of the clustering techniques require the number of clusters to be specified as an input parameter. In preliminary experiments, we tested this by first clustering the Zernike moments using the GK algorithm and three clusters as input. Xie Beni Index was implemented to obtain the optimal number of clusters which gave 2 clusters as the optimal one though there was a very small difference between the values for 2 and 3 clusters. Since single camera images are used here, the activities of walk and stand cannot be differentiated in general; thus, the three major activities (three clusters) were sit, transition (sit-to-stand and stand-to-sit) and upright (stand and walk). As a comparison, we also clustered the Zernike moments using two clusters.

Figures 2 (a) and (b) show the clustering results of one data sequence using an input of 3 and 2 clusters respectively. Figures 2 (c) and (d) show the clustering results with the X Axis indicating the frame number in the sequence and the Y Axis indicating the cluster number after hard partitioning the membership values. The results have been color coded for display purposes. Note that the participant stood up 13 times in this test sequence.

As shown from the results in Figure 2(c), clustering the moments into three clusters did not yield satisfactory results since the data set appeared to form two clusters even visually. The transition frames appeared in both the clusters and did not form a separate cluster. In Figure 2(d), using two clusters, we can see the clean separation with the 13 red regions corresponding to the 13 times the participant stood up during the sequence. Based on these results, we chose to cluster the data into two clusters which yielded good results.

A point to note here is that while it is evident that the two clusters obtained represent the "sit" and "upright" activities, without any prior information, we are unable to identify which cluster indicates which activity. The solution to this is explained in Section IV.C.

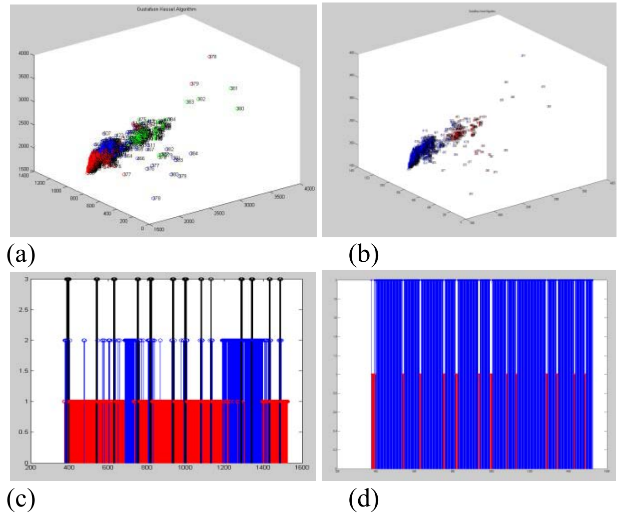


Fig. 2. Test results on a sequence with 13 sit-to-stand motions. GK on Zernike Moments and clustering results into (a) 3 clusters and (b) 2 clusters. (c) 3 cluster results by frame number. (d) 2 cluster results by frame number. In part (d), red corresponds to the upright frames.

### B. *Determining the Set of Image Moments*

To determine the best features for this domain, both the Hu Moments and the Zernike moments (described in Section II) were tested using the GK clustering algorithm. Since we have already established in Section IV.A that clustering with two clusters as input is more effective, we tested the clustering using the two different sets of moments with two clusters as input.

Figures 3(a) and (b) show the clustering results using the Gustafson Kessel algorithm on the Zernike and Hu Moments, respectively. Figures 3(c) and (d) show the clustering results of the two sets of moments by sequential frame number. In this test sequence, the participant walked into the room with the cameras, sat on a chair, stood up and walked out of the room; this was performed 6 times.

By observation, it is apparent that the Zernike Moments have yielded more separable clusters compared to the Hu Moments. The blue color indicates the upright frames and the red color shows the frames where the person is sitting. The blank regions correspond to the absence of the silhouettes, i.e., when the person was not in the room. Figure 3(c) shows an accurate portrayal of the actions in the sequence with the sit frames nestled between the stand frames in six sub runs, whereas the clustering with the Hu Moments is noisy and does not seem to yield a pattern. Based on these results, the Zernike Moments were selected for further testing.

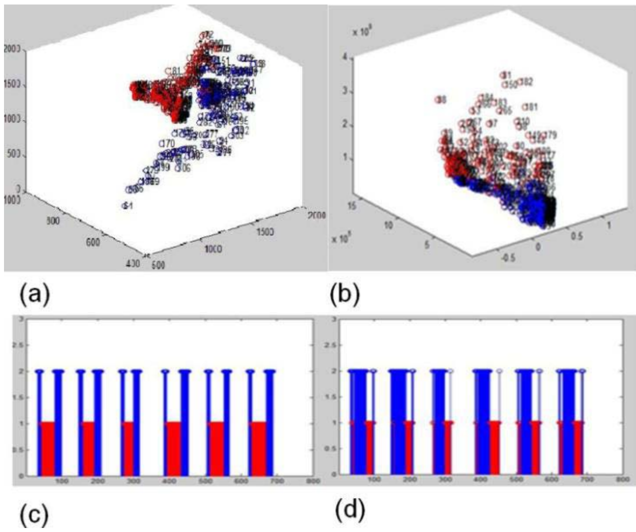


Fig. 3. (a) Test result on a sequence with 6 sit-to-stand motions. GK on Zernike Moments. (b) GK on Hu Moments. (c) Clustering results of Zernike Moments by frame number. (d) Clustering results of Hu Moments by frame number.

### C. *Classifying the Sit-to-Stand Transition Times*

Figure 4 shows the membership values of one cluster by frame number for a test sequence. This particular sequence shows a person sitting, then rising, again sitting and again rising. From the figure, we can see that its membership is initially high, and then it falls to almost zero, and then it again rises. For the frames indicating "transition motion (sit-to-stand or stand-to-sit), the membership is intermediate, approximately in the range of 0.1 to 0.9 in each of the clusters. Note that, if a frame's membership is 0.8 in one cluster, it is 0.2 in the other since there are only two clusters. Thus, by just thresholding the membership values to the range of 0.1 to 0.9, the transition frames representing the sit-to-stand or stand-to-sit motion can be identified. Hence, to identify sit-to-stand or stand-to-sit activity, we do not need to know which cluster represents which activity.

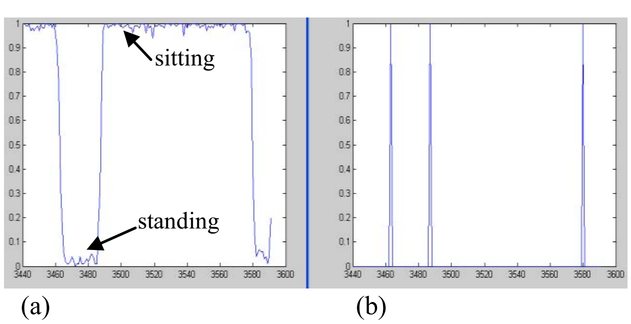


Fig. 4. (a) Membership values of a test sequence by frame number for the sitting activity (b) Transition frames based on thresholding the membership values. The first and third transitions are sit-to-stand motions. The second transition is a stand-to-sit motion.

Figure 5 shows the comparison of the Gustafson Kessel and the Gath and Geva algorithms on a test sequence. This sequence shows a person upright in the beginning and then sitting down and then getting up from his chair four times. As can be seen from the membership values, the sit-to-stand activity is correctly detected with the GK algorithm whereas some of them are lost using the Gath and Geva algorithm.

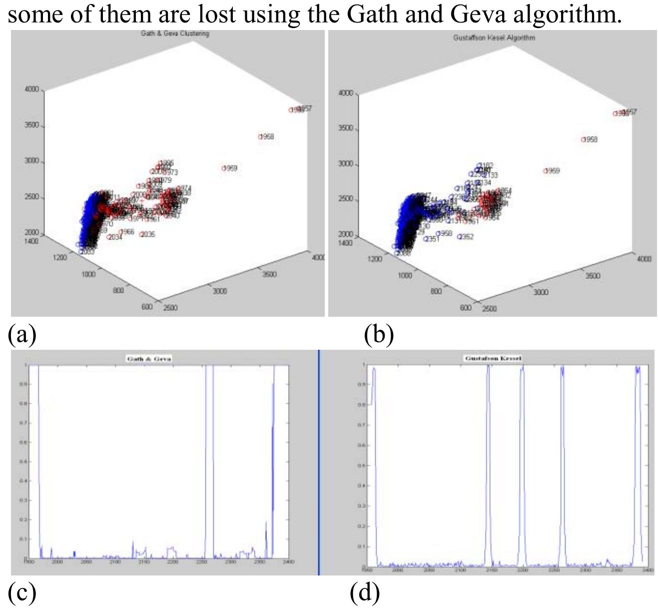


Fig. 5. Clustering results of a test sequence with 4 sit-to-stand motions using (a) the Gath and Geva algorithm and (b) the GK algorithm. (c) Membership values of one cluster by frame number using the Gath and Geva algorithm (d) using the GK algorithm.

### D. *Prototype Matching:*

After using the Gustafson Kessel or any other fuzzy clustering algorithm, we can obtain two clusters. However, without any *a priori* information, there is no way to figure out which cluster indicates which activity. While we could use the fact that most data runs would begin with a person walking into the room thus making the initial frames belong to the "upright" cluster, we wanted to make the algorithm more robust and independent of such *a priori* information. To accomplish this, we followed a semi supervised approach wherein the prototypes of the previous data runs are used to identify the activity cluster of the current data. For the first sequence, the upright and sit clusters were identified manually. For the remaining sequences, the nearest neighbor technique is used to determine whether the cluster belongs to the upright frames or the frames depicting a person sitting.

Figure 6 shows frame examples with the original raw images, the corresponding silhouettes and the classification results for frames indicating sit, sit-to-stand and upright activities. The silhouettes are color coded according to the classified activity. Classification is done by thresholding the membership functions. If the membership value is greater than 0.9, then the frame is assigned to this class. If the membership value is between 0.1 and 0.9 (for both clusters), then the frame is assigned to the transition class.

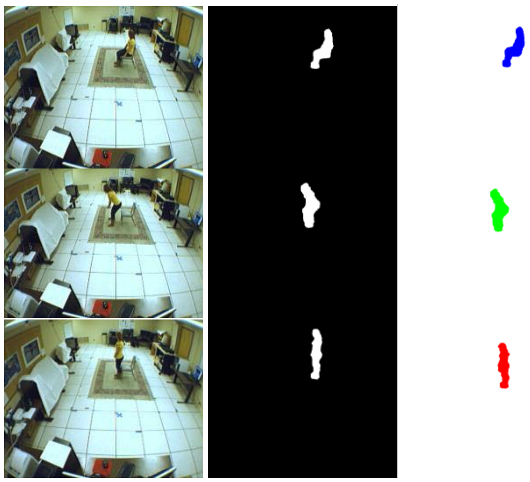

Fig. 6. Segmented activities of a sit-to-stand sequence: Frames 350 (sitting), 355 (transition), and 361 (upright) with the silhouettes and color-coded silhouettes according to the identified activity. Membership values are thresholded from the GK clustering results using the Zernike Moments as features and then classified after prototype matching.

## V. Experiments and results

Experiments were conducted on seven people with ages varying from 18 to 88. Five of the participants were healthy young adults; two elders over the age of 80 participated. The chair used had a standard seat height (approximate 46 cm) as suggested in the Berg Balance Scale test [15]. The video sequence was captured at a rate of 5 frames per second.

To explore the results for a range of sit-to-stand styles, different types of sit-to-stand motions were acted out, including a slouched sit-to-stand which is common as elderly people start bending forward with age, a sideways slouch (both left and right) to depict patients with paralysis, and sit-to-stand with legs away from body to portray patients suffering from knee injuries. Two physical therapists were included in the participant group. They demonstrated the abnormal sit-to-stand motions that show how paralysis, old age and knee injuries affect a person's ability to get up from a chair. Each of these motions was repeated multiple times by each of the five healthy, young subjects. The two healthy, elderly participants were asked to repeat their usual sit-to-stands five times each. In all, 70 runs were taken with 30 of them being the normal healthy runs and the remaining 40 were the elderly or abnormal sit-to-stands mentioned above.

### A. *VICON System for Ground Truth*

The system used as ground truth for the activity analysis is the Vicon Nexus System. Reflective markers were placed on the top of the head, shoulders, on top of the back in line with the shoulders, in the middle of the back and on the feet of the subjects while the experiments were being conducted. This can be seen in Figure 7. These markers allowed the Nexus software to detect the activities of the person while she was walking, standing, sitting or getting up from the chair within the field of view of the camera system.

For our experiment with focus on detection of transition frames, we used only the marker on the head and the markers on the back. The upright and sit frames were identified using height information and also the fact that the back markers and the head marker formed a vertical line. The transition frames were then detected as the intermediate frames between the sit and upright frames. This data provided the ground truth for our experiments.

Fig. 7. An elderly participant with markers on the head, shoulder, two on the back and feet for the VICON motion capture system.

### B. *Classification Results*

As mentioned, various types of sit-to-stand motions were performed by seven different subjects multiple times. Six runs of different kinds of sit-to-stands were processed together and their moments were clustered using the Gustafson Kessel algorithm, the standard fuzzy C means algorithm, and the Gath and Geva clustering algorithm. In order to classify the data into the two activities, "sit" and "upright", the membership values were thresholded so that the frames giving strong membership (> 0.9) in either of the clusters were segmented into their respective activity. If the membership was between 0.1 and 0.9 in each of the two clusters, then the frame was classified as a transition activity (sit-to-stand or stand-to-sit). These results were then compared against the Vicon system results. The fuzzy C means algorithm was implemented to emphasize the problem of using the algorithm on non-spherical data sets.

Figure 8 shows the classification results of the various algorithms for the activities sit, upright, and transition. As can be seen from the figure, in each of the three activities, the Gustafson Kessel technique yields the results closest to the Vicon results. Tables I-III show the confusion matrices for the GK algorithm, the GG technique, and the FCM algorithm, again illustrating the best performance with the GK clustering. The overall activity classification rates are 94.6% for the GK algorithm, 84.2% for the GG algorithm, and 69.8% for the FCM algorithm.

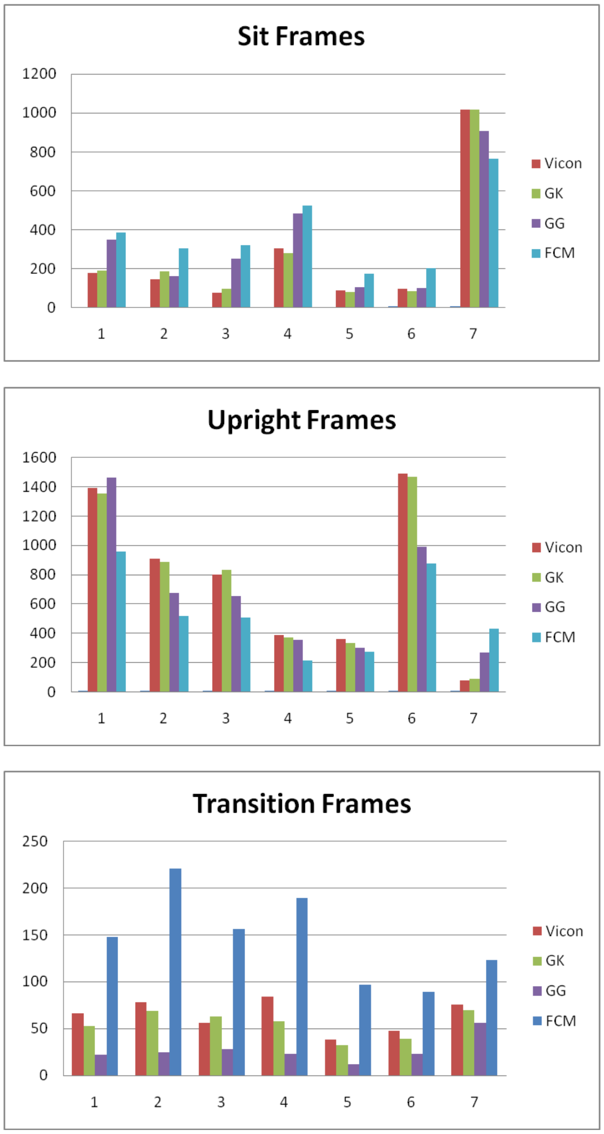


Fig. 8. Classification Results using the Gustafson Kessel (GK), Gath and Geva (GG), Fuzzy C Means (FCM) and Vicon System for Sit, Upright and Transition frames for the seven participants.

TABLE I. CONFUSION MATRIX OF THE GK ALGORITHM FOR ZERNIKE MOMENTS WITH RESPECT TO THE VICON SYSTEM FOR THE ACTIVITIES OF SIT, TRANSITION, AND UPRIGHT.

| GK / VICON | Sit | Transition | Upright |
|---|---|---|---|
| Sit | 1907 | 29 | 7 |
| Transition | 23 | 484 | 38 |
| Upright | 5 | 25 | 5240 |

TABLE II. CONFUSION MATRIX OF THE GG ALGORITHM FOR ZERNIKE MOMENTS WITH RESPECT TO THE VICON SYSTEM FOR THE ACTIVITIES OF SIT, TRANSITION, AND UPRIGHT.

| GG / VICON | Sit | Transition | Upright |
|---|---|---|---|
| Sit | 1692 | 54 | 197 |
| Transition | 223 | 264 | 58 |
| Upright | 363 | 38 | 4839 |

TABLE III. CONFUSION MATRIX OF THE FCM ALGORITHM FOR ZERNIKE MOMENTS WITH RESPECT TO THE VICON SYSTEM FOR THE ACTIVITIES OF SIT, TRANSITION, AND UPRIGHT.

| FCM / VICON | Sit | Transition | Upright |
|---|---|---|---|
| Sit | 1389 | 461 | 93 |
| Transition | 198 | 318 | 29 |
| Upright | 324 | 1015 | 3931 |

## VI. CONCLUSION AND FUTURE WORK

In this paper, we presented a successful and yet simple technique of detecting sit-to-stand transition frames using fuzzy clustering methods. Three clustering algorithms were applied to image moments of extracted silhouettes. A classifier was constructed from the clustering results, and the classification results were compared to ground truth obtained using a Vicon motion capture system. The Zernike Moments were compared with the standard Hu Moments which are much more widely used than the former to indicate the importance of using orthogonal moments in comparison to non-orthogonal ones

It is evident from the results that the Fuzzy C Means clustering algorithm is the least effective of the three algorithms for this domain which is not surprising given that the feature vectors form ellipsoidal clusters as seen in Figure 3(a). The Gustafson Kessel algorithm was shown to work the best for this activity segmentation. The GK algorithm gives results closest to the Vicon system ground truth, making it the most useful clustering technique for our application. Also, the GK algorithm was successful in identifying all of the different kinds of sit-to-stands performed by various individuals of different age groups as well as different sizes.

Experiments are currently being conducted to make the algorithm independent with respect to the location of the camera so that the chair can be at any angle to the camera. Different activities are being added to test the algorithm such as crouching and bending forward and favorable results are achieved. This will make the algorithm more robust and useful for automatic activity recognition in unstructured settings.

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