Design of Fall Detection System: A Dynamic Pattern Approach with Fuzzy Logic and Motion Estimation

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Abstract
Every year thousands of the elderly suffer serious damages such as articular fractures, broken bones and even death due to their fall. Automatic detection of the abnormal walking in people, especially such accidents as the falls in the elderly, based on image processing techniques and computer vision can help develop an efficient system that its implementation in various contexts enables us to monitor people's movements. This paper proposes a new algorithm, which drawing on fuzzy rules in classification of movements as well as the implementation of the motion estimation, allows the rapid processing of the input data. At the testing stage, a large number of video frames received from CASIA, CAVAIR databases and the samples of the elderly's falls in Sabzevar's Mother Nursing Home containing the falls of the elderly were used. The results show that the mean absolute percent error (MAPE), root-mean-square deviation (RMSD) and standard deviation error (SDE) were at an acceptable level. The main shortcoming of other systems is that the elderly need to wear bulky clothes and in case they forget to do so, they will not be able to declare their situation at the time of the fall. Compared to the similar techniques, the implementation of the proposed system in nursing homes and residential areas allow the real time and intelligent monitoring of the people.

Keywords: Video Processing; Gaussian Mixture Model; HSV Conversion; the Elderly's Falls; Fuzzy Inference System; Motion Estimation.

1. Introduction

Today, many countries are faced with the growing population of the elderly each year. In 2000, the elderly aged above 65 constituted one-eighth of the world's population, i.e. a population equivalent to 750 million people [1]. Based on demographics released in 2010, it is estimated that in 2035, one-third of Europe's population will be above 65 years old [2]. Iran is one of the countries with young population and in near future, it has to deal with an aging population. Falls and loss of balance is a common threat to the health of the elderly. It can affect the quality of life, increase maintenance costs, and lead to adverse physical, psychological and social conditions, or even death [3]. Studies show that 25% to 47% of elderly suffer from falls once or more and this figure adds up to 50% among the elderly who live in health care centers. Since this accident can jeopardize the performance and independence of the elderly, the identification of people who are at risk of falling is of paramount importance [5]. Therefore, the first step in the prevention of this incident is to alleviate the side effects of falling [6]. If the elderly are not able to inform people in case of their fall, it might aggravate the damages of this incident and in some cases lead to the loss of their life. Therefore, a smart and efficient system to detect falls of elderly people seems essential. The techniques that have been proposed to date to signify people's falls can be classified into three general categories:

- Sensor networks and wearing sensors.
- The use of gyroscopes, accelerometer and devices for detecting the vibrations caused by falls.
- Monitoring the dynamic state based on video analysis.

In the system designed by Alexander et al. [7] sensor network techniques have been used for monitoring and online surveillance of the elderly. Another technique is employing wireless sensor network and alar system in which the elderly use a button to declare their situation in case of suffering a fall. The main shortcoming of this system is that the elderly need to wear bulky clothes and in case they forget to do so, they will not be able to declare their situation at the time of the fall.

Furthermore, this technique will be inoperable in case the person loses his/her consciousness after the fall. Vibration analysis instruments, gyroscope, status belts and pressure gauge board are other methods designed according to individuals' manner of movement. In 2008, Bourke et al. [9] created a secure threshold for fall detection algorithms which used a biaxial gyroscope. The simultaneous combination of the accelerometer system of the elderly's movement and the estimate of the movement's direction was also proposed by Nyan [10]. The vibration analysis system is also used in detecting the fall of the elderly or the disabled. Among all current systems, the real-time systems which detect the fall of people based on analysis of video images have the highest

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efficiency and accuracy [11]. As to the designing of video surveillance algorithm, Naseimento [12-13] proposed methods based on the analysis of machine vision in detecting changes in individuals' position. In 2012, Liao and Huang [14] detected slips and falls of people based on Bayesian networks. Each of the current systems has strengths and weaknesses with regard to their detection. Low accuracy, low processing speed, lack of real-time response to the events in some of the above cases and high levels of positive error are among the weaknesses of such systems.

2. Methodology

The method proposed for detection of the elderly's falls in this paper draw mainly on video processing techniques to detect the target area. The algorithm has been shown in in Fig. 1 and the main body of the system will be introduced in following sections accordingly.

2.1 Conversion from RGB to HSV space

In many machine vision and image processing algorithms, the intensity of disproportionately high or low light, such as shades in separating a special part of the image, produces error. The color space, which is the result of the removal of unwanted effects of light, is the conversion to HSV space. Using the features of color space in HSV environment can reduce the complexities between the image surface and the intensity of unwanted light which causes errors. In calculation of H section, it is assumed that *M=max (R,G,B), m=min (R,G,B)* and *d=M-m*. The values of r, g and b are also calculated according to *r= (M-R)/d, g= (M-G)/d and b= (M-B)/d*. The main function of frame conversion from RGB into HSV space is minimizing the effects of the individual's shadows in images, which is the major cause of errors in mode separation.

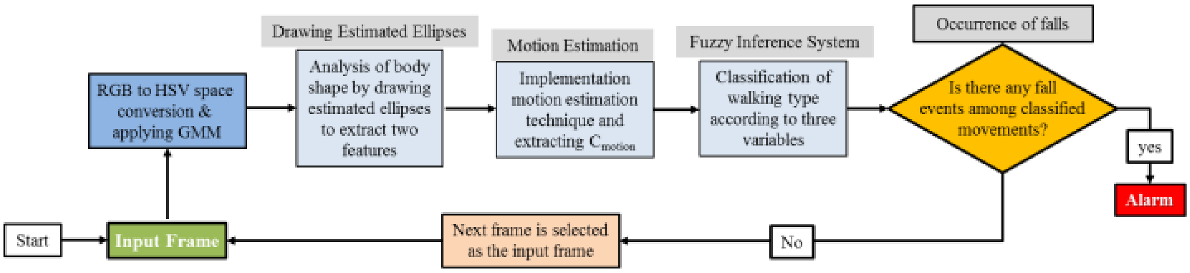

Fig. 1. Proposed algorithm structure

2.2 Adaptive gaussian mixture model (AGMM)

Gaussian Mixture Model (GMM) is a parameter of a probability density function that specifies the weighted sum of Gaussian component densities. This model uses fixation technique to maximize the likelihood or probability for some of the parameters and its function is similar to K-means algorithm. A Pixel *I* at position x and time *t* is modeled as a mixture of K-Gaussian distributions.

The current pixel value in the probability distribution is calculated according to (1):

$$P(I_{t,x}) = \sum_{i=1}^{K} W_{t-1,x,i} * \eta(I_{t,x}, \mu_{t-1,x,i}, \sigma^2_{t-1,x,i}) \quad (1)$$

In this equation, the parameters $W_{t-1,x,i}$, $\mu_{t-1,x,i}$ and $\sigma^2_{t-1,x,i}$ are weight, mean and variance of the i_{th} Gaussian model in the mixture at time *t-1* respectively and also η is a Gaussian probability density function that is obtained as (2):

$$\eta(I,\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{(I-\mu)^2}{2\sigma^2}) \quad (2)$$

The parameter initialization of the weight, the mean and the covariance matrix will be performed using updating producer of k-means algorithm. In this model, the parameters $W_{t-1,x,i}$, $\mu_{t-1,x,i}$ and $\sigma^2_{t-1,x,i}$ are updated based on the new pixel $I_{t,x}$ and the covariance matrix is calculated (3) due to the assumption of independent color components (R, G and B):

$$\sum\nolimits_{t,x,i} = \sigma_{t,x,i} \quad (3)$$

If $I_{t,x}$ is a standard Gaussian, the current pixel called matched or adapted pixel.

$$\left| I_{t,x} - \mu_{t-1,x,i} \right| \le T_{\sigma} \sigma_{t-1,x,i} \quad (4)$$

Matched pixels can be found using this approach and in overall if one of the K Gaussian is adapted, the adapted Gaussian is updated as (5) and (6):

$$\mu_{t,x,i} = (1-\rho)\mu_{t-1,x,i} + \rho(I_{t,x}) \quad (5)$$

$$\sigma^2_{t,x,i} = (1-\rho)\sigma^2_{t-1,x,i} + \rho(I_{t,x} - \mu_{t,x,i})^T (I_{t,x} - \mu_{t,x,i}) \quad (6)$$

In these equations, RAO is defined as a learning rate which changes the converge fast of μ and σ^2 so is combined by known parameters in (7):

$$\rho = \alpha\eta(I_{t,x} | \mu_{t-1,x,i}, \sigma^2_{t-1,x,i}) \quad (7)$$

Similarly, the weights are updated according to the following procedure:

$$W_{t,x,i} = (1-\alpha)W_{t-1,x,i} + \alpha(M_{t,i}) \quad (8)$$

In which $M_{t,i}$=1 is set for the adapted Gaussian and $M_{t,i}$=0 for the others. The learning rate α is used to update the weight and its value ranges between 0 and 1. If none of the K Gaussian component adapts the current pixel value, the least weighted component is replaced by a distribution with the current value as its mean, a high variance, and a low value of weight parameter is chosen as (9) and (10) and finally the weights are normalized as (11) so that $\sum_{i=1}^{K} W_{t,x,i} = 1$:

$$k = \arg\min_{i=1,\dots K} W_{t-1,x,i} \quad (9)$$

$$\mu_{t,x,k} = I_{t,x}, \sigma^2_{t,x,k} = \sigma^2_0, W_{t,x,k} = W_0 \quad (10)$$

$$W_{t,x,i} = W_{t,x,i}(\sum_{i=1}^{K} W_{t,x,i})^{-1} \quad (11)$$

The number of distribution K is estimated according to the w_k divided σ_k merit function and the first distribution of (B) is used as a foreground model. *B* function is calculated according to equation (12) sufficiency:

$$B = \arg\min_b (\sum_{i=1}^{b} W_i > T) \quad (12)$$

In which *T* is the lowest decimal value in the foreground model. During the conversion, the foreground and background are separated. If a pixel *I* do not matches with any one of the background component, then the pixel is marked as foreground. Fig. 2 shows a set of frames taken from a video sequence as well as the application of conversion to HSV space and Gaussian mixture model.

Fig. 2. The person falls on the bed and GMM is applied to separate the moving part of the image in 40 frames with 5 step.

2.3 The anatomical changes of human body during a fall

After separation of the foreground and background of the image, the location and position of the person is identified. The main advantage of this process is the identification of the person's posture relative to the horizontal and vertical axes. After the removal of the additional image pixels and by defining an estimated oval that specifies the position of the person, information about the shape, form and direction of the person's movement can be obtained. In two-dimensional coordinate system, the estimated oval is made of (x, y) center, φ direction and d1 and d2 diameters. When a change in the manner of movement is made, the analysis of two indexes is of paramount importance.

- Standard deviation of the movement direction (η_φ) in the estimated oval.
- Calculating the ratio of d_1 and d_2 as well as standard deviation $\eta_{d1/d2}$.

In Fig. 4 the estimated oval technique is applied on the sample frames (Fig. 3). In this Figure, a set of 9 frames has been shown in which an estimated oval based on the formal mold of a person's body has been depicted.

Fig. 3. Images from left to the right, 135, 140, 145, 150, 155, 160, 165 and 170 frames, and the change of oval based on variation in one's posture has been depicted.

3. Motion Estimation

The important features are extracted from motion estimation that is suitable tools to analysis of motion. Intelligent drawing of estimated ellipse will due to elicit diagonals of ovals and direction of motions. Also motion estimation includes:

A. Motion Vector

The direction of motion based on (13):

$$\delta_j = \frac{1}{I_j}(\sum_{i(x)=1}^{I_j} \delta_{i(x)}, \sum_{i(y)=1}^{I_j} \delta_{i(y)}) \quad (13)$$

Where $\delta_{i(x)}$ and $\delta_{i(y)}$ are horizontal and vertical components (for estimated j^{th} ellipse) in i^{th} frame. *I* is interested area which is segmented from body shape.

B. The Speed of Motion

The speed of motion is calculated by using Euclidian norm between (x_t, y_t) and (x_{t+1}, y_{t+1}).

C. Motion History Image (MHI)

The process of moving in successive frames of a video sequence can be considered as a type of a memory. The person's motion history in the combined image or images, which defines the precedent of the person's movement, is one of the techniques used for displaying the process of movement in the elderly, which according to the binary sequence of the motion area of the person, is modeled based on *D (Pixx , Pixy , t)* taken from the sequence of the main image *I (Pixx , Pixy , t)*.

Each pixel in the images representing the precedent of individual motion by P_{MMI} is shown according to equation

(14) which is, in fact, the temporary memory of movement in each point that occurs in time interval T ($1 \leq T \leq N$) in which N is the number of sample frames in the input video sequence.

$$P_{MMI} = \begin{cases} T & D(Pix_x, Pix_y, t-1) \\ \max(0, P_{MMI}((Pix_x, Pix_y, t-1)) - 1) & otherwise \end{cases} \quad (14)$$

In the frames showing the previous movements, the pixels with higher brightness change show greater motion. To quantify the person's movement, the C_{motion} coefficient is estimated according to motion in frames which is recorded every 500ms. This coefficient is calculated according (15).

$$C_{motion} = \frac{Pix_{CuFrames}}{Pix_{CuFrames} + Pix_{OtherLevels}} \quad (15)$$

This equation is expressed based on pixels belong current frame and other pixels with lower values which is belong on pervious motions in [0-1] range. The motion history image algorithm applied on set of frames of sample clip in Fig. 4.

Fig. 4. Motion History Images (left to right and buttom column) for 95 to 170 frames, 95 to 110 frames, 105 to 120, 115-130, 125-140, 135-150, 145-160, 155-170 frames of a sample video sequence or 132 video frames.

4. Motion Classification Based on Fuzzy Logic Motion Estimation

Fuzzy logic system is effective technique which is based on logical reasoning and uses the concept of degrees awarded to each member or membership function. Fuzzy logic gives an accurate expression of the correct Boolean propositions. In classical logic sets the membership function *u(x)* of an element *x* belonging to a set *A* could take only two values: 1 and 0. In contrast to classical logic sets the membership function of a fuzzy set is in form of a curve which displays how each point of space is mapped to a degree of membership, in other hand, $u_A(x) \in [0,1]$. The proposed fuzzy inference system is composed of three steps that include Fuzzification, Fuzzy rules and inference system and De-fuzzification steps.

4.1 Fuzzification

In the process of fuzzification, membership functions defined on input variables are applied to their actual values so that the degree of truth for each rule premise can be determined. Fuzzy statements in the antecedent are resolved to a degree of membership between 0 and 1 and also membership functions take different shape. We use A trapezoidal membership function in this paper in which is specified by four parameters as *A=trapezoid(x,a,b,c,d)*. This membership function has a flat top and really is just a truncated triangle curve. These straight line membership functions have the advantage of simplicity. This function is described as:

$$A = \begin{cases} 0 & x \leq a \\ (x-a)/(b-a) & x \in (a,b) \\ 1 & x \in (b,c) \\ (d-x)/(d-c) & x \in (c,d) \end{cases} \quad (16)$$

Three member functions for each input are shown in Fig. 5.

4.2 Fuzzy inferencing

To assay the severance of the rule antecedents, we use the *OR* fuzzy operation. Typically, fuzzy expert systems make use of the classical fuzzy operation union:

$$\mu_{A \cup B}(x) = \max [\mu_A(x), \mu_B(x)] \quad (17)$$

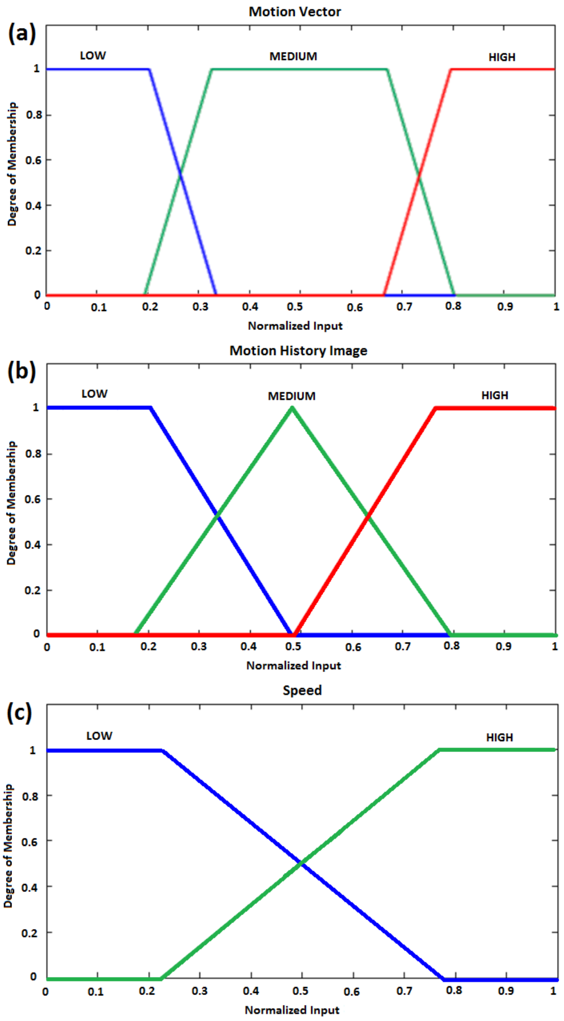

Fig. 5. Inputs of fuzzy model, (a) relative motion vector, (b) relative MHI, and (c) speed.

Similarly, in order to assay the conjunction of the rule antecedents, we apply the *AND* fuzzy operation intersection:

$$\mu_{A\cap B}(x) = \min\left[\mu_A(x), \mu_B(x)\right] \tag{18}$$

Three input variables, which were introduced in the previous section, are directly involved in determining the normal walking of the elderly. Two output variables were also used to indicate its value in decision-making classification of the motion. Five sets of *IF-THEN* fuzzy rules have been shown in Table 1 using an inference system along with a trapezoidal function as the membership functions. The output of the system includes the classification of the normal and abnormal movement's modes, which has been divided into six different intervals. There are three inputs variables *(X_1, X_2, and X_3)* and two outputs *(Y_1, Y_2)* in this inference system.

Table 1. A representation of the rules extracted from fuzzy system

Rules		X_1	X_2	X_3		Y_1	Y_2
1		L	L	L		1	0
2		L	L	M		1	0
3		L	L	H		1	0
4		L	H	L		1	0
5		L	H	M		1	0
6		L	H	H		0	1
7		M	L	L		1	0
8		M	L	M		1	0
9	*If*	M	L	H	*Then*	1	0
10		M	H	L		1	0
11		M	H	M		1	0
12		M	H	H		0	1
13		H	L	L		1	0
14		H	L	M		1	0
15		H	L	H		1	0
16		H	H	L		1	0
17		H	H	M		0	1
18		H	H	H		0	1

4.3 De- Fuzzification

In the final phase, the motion classification based on fuzzy logic is proposed to distinguish the normal or abnormal walking. The last step in the fuzzy inference process is de-fuzzification that helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number. The input for the de-fuzzification procedure is the accumulate output fuzzy set and the output is a single number. We have several de-fuzzification techniques, but the centroid method finds the point where a vertical line would slice the accumulate set into two equal masses. Mathematically this center of gravity (*COG*) can be defined as:

$$COG = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A(x)\,dx} \tag{19}$$

A logical appraise can be obtained by calculating it over a sample of points.

5. Results and Discussion

In three steps, the detection process of a fall in video images was carried out. These three steps were:

- Quantification of movements and modeling accordingly.

When C_{motion} changes from the defined threshold, which has been obtained according to the statistical calculations of video images, the movements similar to the occurrence of a fall can be detected.

- Analysis of the body shape and form in the binary frame

One of the main parameters which will undergo tremendous changes is η_φ or standard deviation in the direction of motion. In average, of 96 tested video sequences, η_φ was about 15 degree and the ratio of $\eta_{d1/d2}$ was 0/9.

- The inactivity of the elderly after the fall.

The parameters that might change after a fall or during inactivity of the person are expressed as follow:

- C_{motion}< 5%
- Standard deviations η_x and η_y which are both smaller than 2.
- Standard deviations in the estimated oval equations, which under conditions η_{d1}<2, η_{d2}<2 and η_{φ}<15^o shows the inactivity or stillness of the elderly after suffering from a fall.

To evaluate the performance of the proposed system, the behavioral model of detection algorithm is simulated based on the criteria of valuation where the outputs have been compared to reality. Also, the model of inferred motion is verified using actual measured values as inputs.

The system was implemented on set of video sequences taken from CASIA, CAVAIR databases [15-16] and the samples of the elderly's falls in Sabzevar's Mother Nursing Home containing the occurrence of the falls, abnormal gate and normal gate in Iran. All sequences were randomly converted into 4 categories of Movie with these details: AVI format, 120×160 pixels resolution and 15 fps.

To examine the performance of developed models, various criteria are used to calculate errors. In the next equations, F_k shows the real value of the variable being modeled or forcasted (observed data), and A_k is the real mean value of the variable and N is the number of test observations [17]. In Fig. 6, the performance of proposed system is dedicated for original walking and predicted posture of walking in sample time.

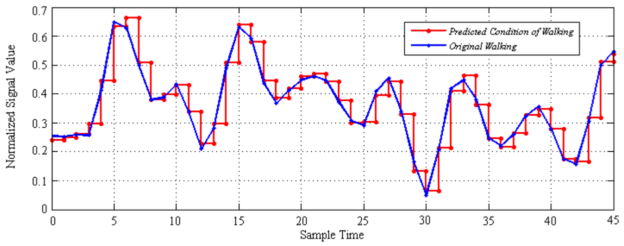

Fig. 6 Results for fuzzy predictor for various posture of walking among normal walking and abnormal walking like falling

The *MAPE* (Mean Absolute Percent Error) proposes the size of the error in percentage terms. It is calculated as the average of the unsigned percentage error, as shown in the (20):

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\frac{|F_k - A_k|}{A_k} \tag{20}$$

The root-mean-square deviation (*RMSD*) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed [17]. Basically, the *RMSD* represents the sample standard deviation of the differences between predicted values and observed values as (21).

$$RMSD = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(F_k - A_k)^2} \tag{21}$$

Standard deviation error (*SDE*), according to (22), indicates the persistent error even after calibration of the model.

$$SDE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{|F_k - A_k|}{A_k} - \frac{MAPE}{100}\right)^2} \tag{22}$$

Errors in modeling with considering *MAPE*, *RMSD* and *SDE* are summarized in Table 2 so that the error rate is minimal and the proposed algorithm not only has the capability to classify, but fuzzy system can also act as a good walking predictor. In this table, the threshold of falling is assigned for different postures and different angles of walking. Accelerometers and vibration analysis systems are facing with the sensitivity between 90%-95% and specificity higher than 95%. While the sensitivity and specificity of the algorithm based on machine vision is respectively 85-95% and 90%-100% [18-24].

Table 2. The received video sequences, calculation of MAPE, RMSD, SDE and Precision of the proposed algorithm

	Input Parameters			**Error Criteria**			
	On MV parameter	On MHI parameter	On Speed parameter	MAPE (%)	RMSD	SDE	Precision (%)
Threshold Value	0.2	-	-	3.5708	0.0128	0.0379	96.42
	0.27	-	-	4.8461	0.0172	0.0510	95.15
	0.34	-	-	5.5545	0.0197	0.0583	94.44
	0.67	-	-	5.9079	0.0637	0.1406	94.09
	0.74	-	-	6.3717	0.0645	0.1425	93.62
	0.8	-	-	7.0675	0.0657	0.1459	92.93
	0.27	0.35	-	6.8614	0.0601	0.1332	93.13
	0.74	0.35	-	7.9326	0.0595	0.1336	92.06
	0.27	0.65	-	8.6511	0.0594	0.1346	91.34
	0.74	0.65	-	9.3696	0.0594	0.1361	90.63
	0.27	0.35	0.5	8.3842	0.0682	0.1532	91.61
	0.74	0.35	0.5	9.0926	0.0695	0.1570	90.90
	0.27	0.65	0.5	10.0881	0.0596	0.1382	89.91
	0.74	0.65	0.5	10.5671	0.0597	0.1400	89.43
Mean Value	*If* T=0.35			4.4210	0.0157	0.0466	95.57
	If T=0.5			7.5382	0.0267	0.0788	92.46
	If T=0.65			10.0887	0.0357	0.1053	89.91

Therefore, systems based on machine vision techniques in terms of accuracy and sensitivity is competitive in performance compared to other techniques such as sensor network and accelerometers and vibration analysis systems. Unlike other techniques, the method of video processing has the advantage which is doing intelligent monitoring of the elderly person and is comfortable wearing heavy clothing.

6. Conclusions

Based on the analysis of video sequences, using machine vision and fuzzy logic, the proposed system detects the occurrence of the falls with higher precision and lower SDE. The practical results and final simulation of the algorithm showed that the system, though using a single camera to capture the movements of the elderly, produced higher sensitivity and specificity compared to similar methods. 93% accuracy, low mean absolute percent error (MAPE) and high detection rate have dramatically increased the reliability of the system performance. The accurate prediction of the fall of the elderly based on the analysis of video images will be among the future researches of the author. It would be based upon motion equations and biomechanics joints of the elderly.

References

[1] Newton, R.A. "Standing balance abilities of elderly subjects under altered visual and support surface conditions", Physical therapy Canada, Vol. 47, No. 1, 1995, pp. 25-29.

[2] Ambient Assisted Living Joint Programme (2008), available from http://www.aal-europe.eu.

[3] Fife, T.D., Zwerling, L., Socotch, T., Jacobson, K., Bell, T., Beykirch, K. "Compassion of Static and Dynamic Posture Graphy in Young and Older Normal People", Journal of American Geriatric Society, Vol. 42, No. 4, 2000, pp. 405-412.

[4] Wegner, L., Kisner, C., Nichols, D. "Static and Dynamic Balance Response in Persons with Bilateral Knee Osteoartherritis", Journal of Orthopaedic and Sports Physical Therapy, Vol. 25, No. 1, 1997, pp. 13-18.

[5] Atwater, S.L., Crawe, T.K., Deitz, J.C., Richardson, P.K. "Inter Rater and Test-Restart Reliability of Two Predictive Balance Tests", Physical Therapy, Vol. 70, No. 2, pp. 79-87.

[6] Satterfied, K.S. "Balance Testing Helps Identify Elderly at Risk of Multiple Falls", American Otological Society, May 2001.

[7] DirectAlert (2010). Wireless emergency response system. URL: http://www.directalert.ca/emergency/help-button.php.

[8] Alexander, G.L., Rantz, M., Skubic, M., Aud, M.A., Wakefield, B., Florea, E., Paul, A. "Sensor systems for monitoring functional status in assisted living facility residents", Research in Gerontological Nursing, Vol. 1 No. 4, 2008, pp. 238-244.

[9] Bourke, A.K., Lyons, G.M. "A threshold-based fall-detection algorithm using a bi-axial gyroscope sensor", Medical Engineering and Physics, Vol. 30, No. 1, 2008, pp. 84–90.

[10] Nyan, M., Tay, F.E., Murugasu, E. "A wearable system for pre-impact fall detection", Journal of Biomechanics, Vol. 41, No. 16, 2008, pp. 3475–3481.

[11] Rezaee, K., Haddadnia, J., Delbari, A., Madanian. M. "Predicting and Monitoring of the Elderly Falls Based on Modeling of the Motion Patterns Obtained from Video Sequences", Iranian Journal of Aging, Vol. 8, No. 28, 2014, pp. 15-21.

[12] Nascimento, J.C., Marques, J.S. "Performance evaluation of object detection algorithms for video surveillance", IEEE Transactions on Multimedia, Vol. 8, No. 4, 2006 pp. 761–74.

[13] Rezaee, K., Haddadnia, J., Delbari, A. "Intelligent Detection of the Falls in the Elderly Using Fuzzy Inference System and Video-based Motion Estimation Method", The 8th Iranian Conference on Machine Vision and Image Processing, 2013.

[14] Liao, Y.T., Huang, C.L., Hsu S.H. "Slip and fall event detection using Bayesian Belief Network", Pattern Recognition, Vol. 45, No.1, 2012, pp. 24–32.

[15] Yu, S., Tan, D., Tan, T. "A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition", in: Proc. of IEEE International Conference on Pattern Recognition, Vol. 4, Hong Kong, China, 2006, pp.441–444.

[16] Auvinet, E., Rougier, C., Meunier, J., St-Arnaud, A., Rousseau, J. "Multiple cameras fall dataset", Technical report 1350, DIRO - Université de Montréal, July 2010.

[17] Hyndman, Rob J., Koehler, Anne B. "Another look at measures of forecast accuracy". International Journal of Forecasting, Vol. 22, No. 4, 2006, pp. 679–688.

[18] Tyrer, H.W., Alwan, M., Demiris, G., He, Z. "Technology for successful ageing", Proceedings of the 28th IEEE Annual International Conference, 2006.

[19] Zhang, T., Wang, J., Liu, P., Hou, J. "Fall Detection by Embedding an Accelerometer in Cellphone and Using KFD Algorithm", International Journal of Computer Science and Network Security. Vol. 6, No. 10, 2006, pp. 277-284.

[20] Rougier, J., Meunier, J., St-Arnaud, A., Rousseau, J. "Fall detection from human shape and Motion history using video surveillance", In: International on Advanced Information Networking and Applications Workshops, 21-23 May 2007, pp. 875-880.

[21] Vishwakarma, V., Mandal, C.A., Sural, S. "Automatic detection of human fall in video", In: International Conference on Pattern Recognition and Machine Intelligence, 2007, pp. 616–23.

[22] Tao, J., Turjo, M., Wong M-F, Wang, M., Tan, Y-P. "Fall incidents detection for intelligent video surveillance", In: Proceedings of the Fifth International Conference On Information, Communications and Signal Conference Processing, 2005, pp.1590–4.

[23] Shieh, W.Y., Huang, J.C. "Falling-incident detection and throughput Enhancement in a multi-camera video-surveillance system", Medical Engineering & Physics, Vol. 10, No. 16, 2011, pp. 28-38.

[24] Rezaee Kh., Ghezelbash M.R., Haddadnia J., Delbari A. "An Intelligent Surveillance System for Falling Elderly Detection Based on Video Sequences", 19th Iranian Conference of Biomedical Engineering (ICBME), Tehran, Iran, 20-21 December 2012.

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