A new Framework for Elderly Fall Detection Using Coupled Hidden Markov Models

Mabrouka Hagui[1], Mohamed Mahjoub[1], and Faycel ElAyeb[2]
[1]National Engineering School of Sousse, University of Sousse, Laboratory of Advanced Technology and Intelligent Systems, Tunisia
[2]Preparatory Institute for Engineering Studies, University of Monastir, Tunisia

Abstract: *Falls are a most common problem for old people. They can result in dangerous consequences even death. Many recent works have presented different approaches to detect fall and prevent dangerous outcomes. In this paper, human fall detection from video streams based on a Coupled Hidden Markov Model (CHMM) has been proposed. The CHMM was used to model the motion and static spatial characteristic of human silhouette. The validity of current proposed method was demonstrated with experiments on Le2i database, Weizman database and video from Youtube simulating falls and normal activities. Experimental results showed the superiority of the CHMM for video fall detection.*

Keywords: *Fall detection; feature extraction; shape deformation, motion history of image, coupled hidden markov models.*

Received June 17, 2016; accepted July 28, 2016

1. Introduction

Falls are the most common problem for old persons all over the world. In fact, according to Centers for Disease Control and Prevention, each year, one in every three adults age 65 and older falls. Therefore, automatic method for falls can be useful for the security and the safety of these persons. Current studies on fall detection have employed a variety of techniques and methods that can be classified in three categories: wearable device based approach, ambient device based approach and camera vision.

Wearable device based approaches evaluate the activity of the person. They measure the acceleration of the body or its parts using accelerometers. The fall is detected when the negative acceleration is increased. These approaches can also combine the use of accelerometers and postures sensors to identify the fall.

The second approach is based on ambient device [3] attempt to fuse visual and audio data and event sensing through vibration data collected by multiple sensors installed in a closed room/area and a dedicated Personal Computer (PC).

Recently, the third approach is increasingly used as it presents multiple advantages over the other two methods. First, cameras can be used to detect multiple events simultaneously with less intrusion. Then, the old person can move independently without wearing medical devices.

The purpose of the present paper is to present a new method for fall detection based on Coupled Hidden Markov Models (CHMMs). Our proposed system consists of the following steps: silhouette extraction, feature extraction, classification and modeling using CHMMs. The system starts by removing the background and extracting binary human silhouette which will be the input of the next step. For the feature extraction, we choose to fuse static and motion characteristics of the moving person in order to improve the performance of fall detection. Here, we used the ratio of bounding human box and the motion history of image.

Next, we will begin with an overview of previous work in section 2. Section 3 presents our proposed method for fall detection. In section 4 the presented method is tested and compared for the fall detection. Section 5 summarizes our results and discusses the possible topics for future works.

2. Related Work

Falls are a principle cause of fatal injury especially for the elderly. It has become important to develop automatic system to detect falls in order to rapidly react and avoid dangerous outcomes. In [3, 4, 12, 15, 21] researchers have presented a survey on fall types and the methods used to detect this event.

Many works have showed that elderly monitoring through video surveillance may be the regular solution used in clinics or nursing institutes. This approach analyses the human activities using image processing and video vision techniques.

In [20], authors have presented a new approach for human fall detection. This approach starts by subtracting the background to detect a moving object and extract it with its minimum-bounding box. Then, a fall model is used to analyze the video sequences. This model is composed of two steps: fall detection and fall confirmation. It employs three features.

Initially aspect ratios, horizontal and vertical gradient values of an object are utilized to detect fall. Then fall angle is applied for fall confirmation.

Authors in [1, 5, 6, 23] have presented a new method to detect falls by analyzing human shape deformation during a video sequence. The proposed system in [1] extracts the person's silhouette from each frame and then the shape deformation is quantified from these silhouettes based on shape analysis methods. Falls are detected from normal activities using a Gaussian mixture model.

In [17], they have proposed a new approach to detect unintentional falls. The proposed approach is based on a combination of motion gradients and human shape features variation.

Zerrouki and Houacine [24] have proposed a new approach for classifying human body postures based on the Truncated Singular Value Decomposition (SVD) coefficients using an Artificial Neural Network.

Other recent methods [9, 14, 21] are interested in modeling the motion of part of the body using Dynamic Bayesian Network (DBN), Hidden Markov Model (HMM) and neural network.

In [14], they have presented a method for fall detection integrating multiple modalities. This method generates the background which will be subtracted from each frame to detect moving objects. Then they calculated the aspect ratio of the minimum bounding box obtained using connected component analysis. They haveemployed a fusion of audio and video data to reach a final decision of human fall using HMM.

Tong *et al*. [21] have presented HMM-based method using tri-axial accelerations of human body to detect and predict falls. Also Lim *et al*. [13] have proposed to combine a simple threshold and HMM using 3-axis acceleration.

Authors in [10], have proposed new HMM based method that combines both audio and video descriptors to detect falling event.

In [20], a new approach for fall detection based on Hierarchical Hidden Markov Model with two layers has been proposed. The states of the first one correspond to the person's body poses. The extracted characteristics consist of the image angle sequences of the detected human blob, in the 3D world.

Zhang and Swachuk [25] have proposed in a new fall detection framework that includes fall detection algorithms with context information using a Bayesian network. They used different sensors to measure the context information that can include physiological measurements (such as respiration, blood pressure, heart rate, etc.,), physical activity level and location.

Authors in [2] have presented a new method for video fall detection using a neural network. The intelligent proposed detector analyses the binary image of the person and try to identify which plausible situation the person was in at particular slice of time.

3. Proposed Method

In our proposed probabilistic framework, the video will be represented by a coupled HMM which is a dynamic graphical tool indicating the dependence between nodes in intra and inter slice.

Our proposed system, as illustrated in Figure1, starts by generating the background which will be subtracted from each frame to extract the foreground moving object. Then morphologic operations and filtering are done in order to remove shadow and construct the human silhouette. After that, static and motion features will be extracted and quantified. The result of this step will be the input of the CHMM which will classify the event.

In this section, we introduce the principles and the theory of the chosen descriptors. Then we present an overview of coupled HMM model and how our system detect fall.

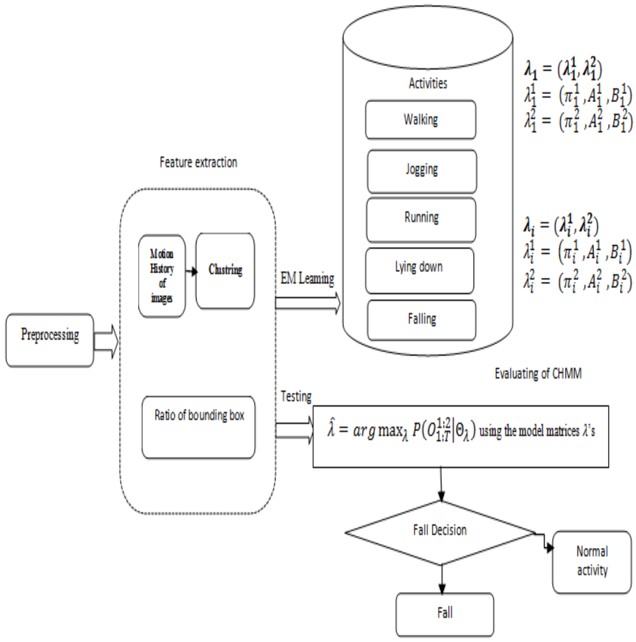


Figure 1. Conceptual diagram of the proposed system.

3.1. Preprocessing

Firstly, our system starts by extracting the moving object from the video input. To achieve this task, we have employed the grimson and stauffer method given in [19] to generate the background.

This method is based on an efficient algorithm using adaptive Gaussian mixture probability density. It models each pixel separately as a mixture of k Gaussians as follow:

$$P(X_t) = \sum_{i=1}^{k} w_{i,t}\, \eta(X_t; \mu_{i,t}; \Sigma_{i,t}) \qquad (1)$$

Where $w_{i,t}$, $\mu_{i,t}$,$\Sigma_{i,t}$are an estimate respectively of the weight, mean and covariance matrix of the i^{th}

Gaussian at time t. η correspond to the normal probability density function.

The Gaussians are evaluated for each frame to determine which are most probably to represent the background. Then the pixels which do not fit the background Gaussians are considered foreground pixels. The method uses on-line recursive equations to update parameters estimation of the Gaussians as following:

If X_t is within λ standard deviations of then the i^{th} Gaussian is updated as follows:

$$w_{i,t} = w_{i,t-1} \quad (2)$$

$$\mu_{i,t} = (1-\rho)\mu_{i,t-1} + \rho X_t \quad (3)$$

$$\sigma_{i,t}^2 = (1-\rho)\sigma_{i,t-1}^2 + \rho\left(X_t - \mu_{i,t}\right)^T (X_t - \mu_{i,t}) \quad (4)$$

Where $\rho = \alpha P(X_t; \mu_{i,t-1}; \Sigma_{i,t-1})$and $\alpha$is a learning constant.

The rest of Gaussians are updated by:

$$w_{i,t} = (1-\alpha) w_{i,t-1} \quad (5)$$

$$\mu_{i,t} = \mu_{i,t-1} \quad (6)$$

$$\sigma_{i,t}^2 = \sigma_{i,t-1}^2 \quad (7)$$

In the case X_t does not fit any Gaussians, the least probably Gaussian is replaced with a new one which has $\mu_{i,t} = X_t$, $\Sigma_{i,t}$ large and $w_{i,t}$low.

To identify Background Gaussians and foreground ones, all Gaussians are sorted in the decreasing order by the value of $W_{i,t}/\|\Sigma_{i,t}\|$. Hence, Gaussians with larger weight and low variance are assumed to be background.

For some threshold T, the proportion of the scene that should be considered as the background, the set $\{1..B\}$ of background Gaussians is obtained by:

$$B = arg\min_b\left(\left(\frac{\sum_{i=1}^{b} w_{i,t}}{\sum_{i=1}^{k} w_{i,t}}\right) > T\right) \quad (8)$$

So if $X_t$does not fit one of these B Gaussians, the pixel is marked as foreground. Foreground pixels are then grouped into regions using 2D connected component labeling. Detected regions are tracked from frame to frame. The resulted silhouettes contain noisy area and shadow. This is due to the fact that each pixel is modeled independently of its neighbor's pixels. To improve the result, we use morphological filter called Filter Alternate Sequential [18]. It is composed of morphological openings and closings whose basic morphological operations are dilation and erosion. This filter is specifically designed to remove unwanted image components and/or enhance wanted ones. This is of great interest in our work as we want to suppress noise and small objects and at the same time enhance moving objects detected.

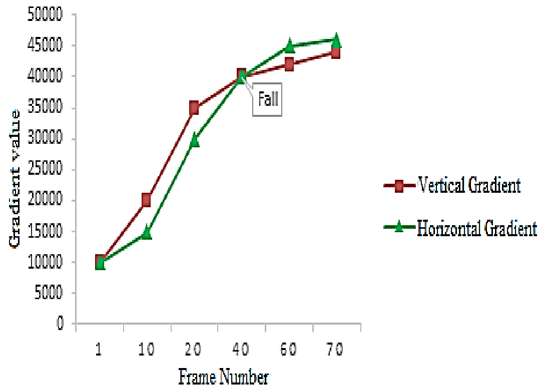
The use of the Grimson and Stauffer method described above followed by the application of morphological filter give acceptable result of real time tracking. The Figure 2 presents current frame, the generated background and the human silhouette after background subtracting. After repairing the noisy silhouette, the next step is to eliminate the size difference caused by the difference distance between the camera and the moving object; the silhouettes are centered and adjusted to the same height.

a) Current frame. b) Generated background. c) Foreground moving object.

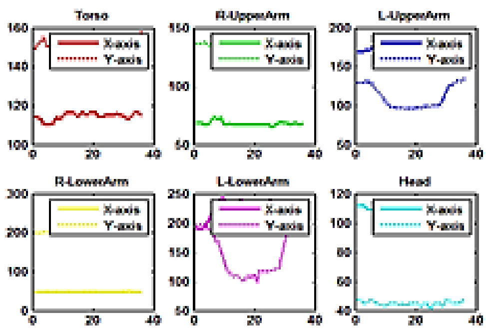
Figure 2. Silhouette extraction.

3.2. Features Extraction

Different features are used in literature to detect fall by analyzing video such as vertical and horizontal gradient, motion history of image, shape analysis and posture. We have made a comparison between these used features in order to select the appropriate ones to employ for training our coupled hidden Markov Models and to detect fall. The Figure 3 shows the variation of the horizontal and vertical gradient (a) and the variation of the posture of the different body parts (b) during the falling sequence.



a) Horizontal, vertical gradient variation.



b) Posture variation.

Figure 3. Example of gradient and posture variation during fall.

We have employed the two concepts sensitivity and specificity defined by the Equations (13) and (14) to compare the performance of these features.

The result of the comparison in best case is indicated in the Table 1:

Table 1. Features comparison.

Method	Sensitivity (%)	Specificity (%)
Vertical and Horizontal gradient	92	89
Motion History image	90	75
Shape deformation	96	87
Shape deformation + Motion History	97	90
Posture	92	90

Our investigation of many proposed methods for the fall detection shows that combination of temporal and static features gives important results.

Our presented system combines motion history and shape analysis to detect fall. The combination of these two features has presented interesting results as indicated in [8].

3.2.1. Motion History Image

Motion History Image (MHI) as presented in [13] and [22] is a temporal method which is robust in representing movements. Each element of the MHI H_τ is a function of the temporal history of movement at that point, happing for the duration τ (with $1 \leq \tau \leq N$ for a sequence of length N frames) as indicated in Equation (9):

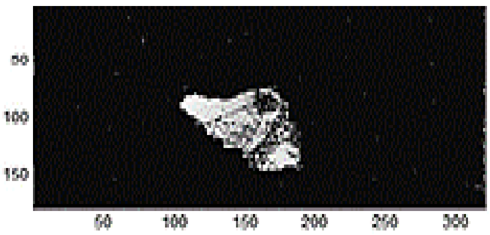
$$H_\tau(x;y;t) = \begin{cases} \tau & if\ D(x,y,t) = 1 \\ \max(0;(H_\tau(x;y;t-1)-1)) & otherwise \end{cases} \quad (9)$$

Where $D(x;\ y;\ t)$ is a binary image sequence specifying the moving regions obtained by image-differencing method.

The more recent moving pixels in Motion History Image are brighter. A fall generally occurs with a large motion.

Figure 4 represents (b) motion history of an image sequence simulating a human falls (a).

a) Image frames of fall.



b) Motion of History.

Figure 4. Example fall frames with MHI features.

3.2.2. Human SHAPE Analysis

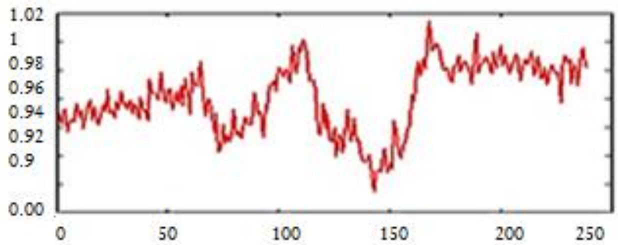
These features are used to analyze the global motion orientation of object. The technique computes the width and the height of the foreground's object in each frame. After that two parameters are computed in order to classify different human activities. Suppose w is the width of the foreground object's bounding box in the nth frame and the height is h

The feature to extract is given by Equation (10):

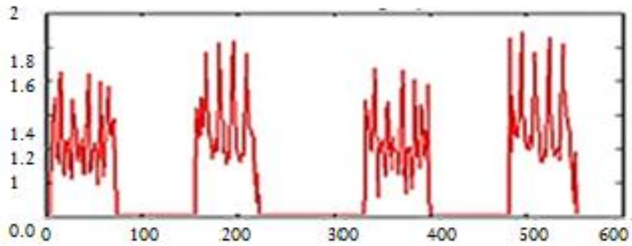
$$\alpha = \frac{w}{h} \quad (10)$$

The ratio of the bounding box α is employed to distinguish between standing and lengthen postures.

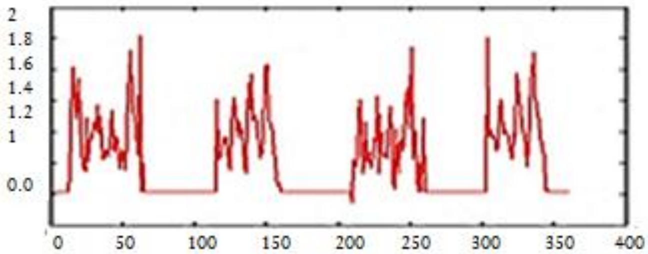
Figure 5 presents the resultant ratio curves from different event process, walking, running, jogging or falling that distinction among them. For instance, the curve in (a) shows that the biggest variation of the ratio is indicated during fall process. The three others process can be considered as periodic cycles.



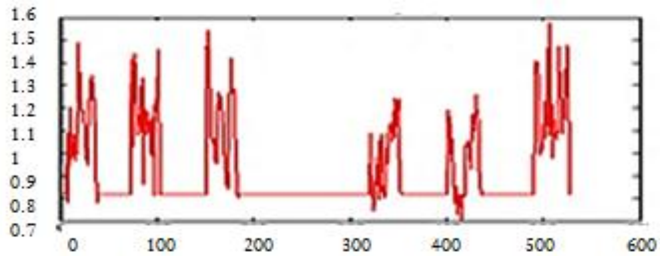
a) video containing Fall.



b) walking sequence.



c) Jogging sequence.



d) running sequence.

Figure 5. Example of ratio variations.

3.3. Clustring

After extracting the motion and static features, we identify clusters of data which will correspond to the state of the CHMM. We employ the k-means algorithm. Firstly, the system selects a set of the center of cluster. Then the distance of each feature vector from these centers is found and each vector is associated with the cluster having the nearest center. Then this task is repeated again until a convergence criterion is met. When the realization of the codebook is achieved, the index number of the code words is used as input of CHMM.

To choose the adequate number of clusters, we plot the variation of the mean silhouette of the motion history.

The principles of this method is to plot the percentage of variance explained by the clusters against the number of clusters, the first clusters will add much information (explain a lot of variance), but at some point the marginal gain will drop, giving an angle in the graph. The number of clusters is chosen at this point, hence.

Figure 6 shows that the silhouette coefficient was highest when the number of the cluster k=3 for the three process walking, running and falling. So, we suggest that's the optimal number of clusters.

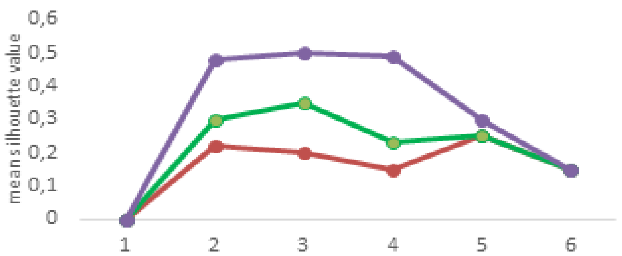


Figure 6. Mean silhouette variation.

3.4. Coupled Hidden Markov Model

The fall detection model should take in consideration the dependency between motion and human shape deformation because they are derived from the same movement of body parts. The CHMM can be used to model this event.

Figure 7 shows a CHMM and it marks the interaction between neighbor variables.

The empty ellipses describe the hidden nodes and the colored ones are the observations.

The hidden nodes X_1 model the static spatial-temporal feature. It is associated with one observation which corresponds to human shape deformation feature, the ratio α. The hidden node X_2 models the motion feature. It is linked with the feature of motion history of image MHI.

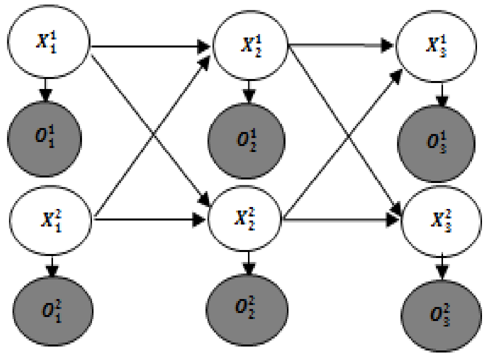


Figure 7. Coupled Hidden Markov with two chains.

Our proposed new coupled HMM models can be characterized by a set of elements $\lambda = (\pi, A, B)$ where:

- Prior probability $\lambda = (\pi, A, B)$where $\sum_j \pi_j^i = 1 \ \forall\, i = 1,2$ *and* $\pi_j^i = p(q_t^i = j)$
- Transition probability $A = \{a^1_{i,j}, a^2_{i,j}\}$ where $\sum_j a_j^i = 1 \ \ \forall\, i = 1,2$
- Observation probability $B = \{b_j^1(k), b_j^2(k)\}$, $1 \le k \le M$where $\sum_{k=1}^{M} b_j^i(k) = 1 \qquad \forall\, i = 1,2$

3.4.1. Inference

Here, we try to compute the marginal probability over our CHMM $P(X_i|O_{1:T})$ of hidden variables X_i given an observation sequence $O_{1:T}$.

There are two kinds of inference algorithms: exact and approximate algorithms. We will use the same structure of BN during all the slice, the number of hidden nodes is two and the values of observations is discrete so we can use the exact Inference. The commonly used algorithm for the exact inference is the Junction Tree (JTree) inference algorithm [16]. Our proposed system will use this algorithm to compute the full joint probability for the DBN which can be factored into product of local conditional probabilities as indicated in Equation (11):

$$P(X^{1:2}_{1:T}, O^{1:2}_{1:T}) = P(O^{1:2}_{1:T}|X^{1:2}_{1:T})P(O^{1:2}_{1:T}) \qquad (11)$$

Where $X^{1:2}_{1:T} = \begin{bmatrix}X_1^1\\ X_1^2\end{bmatrix} \dots \begin{bmatrix}X_T^1\\ X_T^2\end{bmatrix}$and $O^{1:2}_{1:T} = \begin{bmatrix}O_1^1\\ O_1^2\end{bmatrix} \dots \begin{bmatrix}O_T^1\\ O_T^2\end{bmatrix}$

3.4.2. Learning Parameter

Here, the task is to find the optimal parameters Θ, i.e., to specify the Conditional Probability Distribution (CPD) at each node. If the variables are discrete, it can be represented by a table CPT. CPTs and CPDs compute the maximum likelihood over the training data. The structure of our proposed CHMM is known, it includes only two hidden nodes so the EM algorithm can be used to achieve the parameter learning. The EM applies iteratively two steps: Expectation-step and Maximization step [11, 16].

The Expectation-step computes the conditional expectation of the log-likelihood function given the observed data O and the current parameter $\theta(t)$.

The M-step supposes that the distribution found in the E-step is correct and try to locate a new parameter that maximizes the likely log-likelihood.

3.4.3. Fall Detection

In general, fall detection involves determining the class of the current event: walking, running, lying down or falling. To resolve this problem, we compute the maximum likelihood of the input sequence over the trained data. The event classification is done by the application of the following Equation:

$$\hat{\lambda} = arg \max_{\lambda} P(O_{1:T}^{1:2}|\Theta_\lambda) \tag{12}$$

The parameter vectorθ_λ includes prior probability, transition probability and the observations probability distributions.

4. Experiments

We evaluate the performance of the proposed method by considering detection rate, false positive rate and misdetection rate.

4.1. Data Description

The performance of the proposed methods was evaluated using 50 video clips from Le2i databases [22], Weizman dataset [7] and from the YouTube. The used video clips contain 30 sequences simulating human falls and 20 others enclose normal activity such as walking, jogging, sitting down, lying down and running.

The main assumptions made in this work, were that:

- The foreground in the video sequence contains only one person.
- The camera position was fixed through all the video capture in order to be able to perform frame subtraction.

4.2. Experimental Results

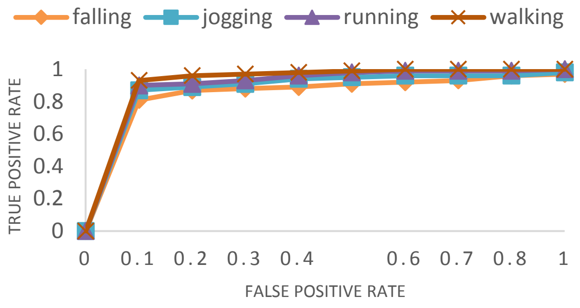
Fall detection is either positive if the automatic method properly recognizes a fall, or negative if it does not. There are four possibilities:

- True Positive (TP): a fall happens; the system detects it.
- False Positive (FP): the system declares a fall, but it did not occur.
- True Negative (TN): a normal event is produced; the system does not affirm a fall.
- False Negative (FN): a fall occurs but the system does not detect it.

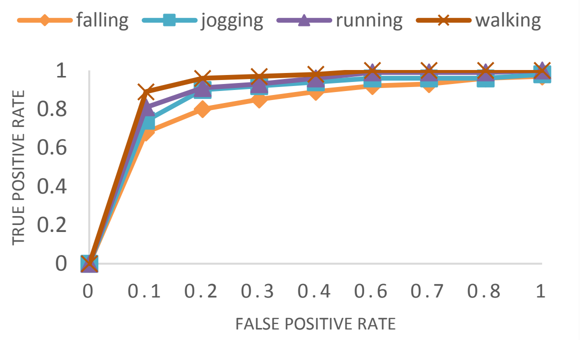
To evaluate the performance of our CHMM, we use the ROC curve presented in Figure 6 which plot the variation of the two couple sensitivity and specificity defined by the following Equations:

$$sensitivity = \frac{TP}{TP+FN} \tag{13}$$

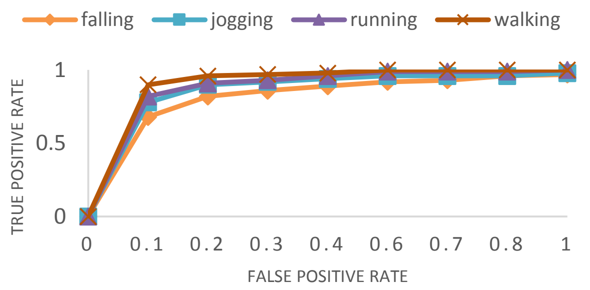
$$Specificity = \frac{TN}{TN+FP} \tag{14}$$



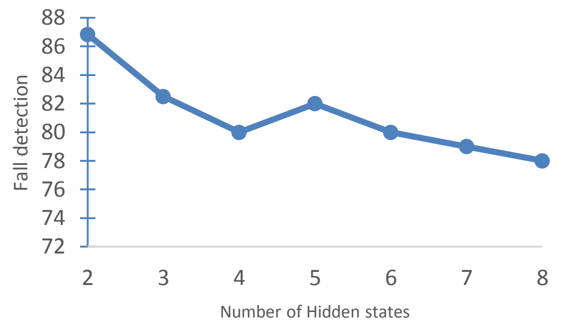
a) Number of hidden states=2.



b) Number of hidden states=4.



c) Number of hidden states=5.



d) Fall detection rate.

Figure 8. Performance evaluation using Roc curve.

The Figure 8 shows the performance evaluation of our proposed system for events classification (fall detection) using different number of the hidden states. The Figure (8-d) describes the variation of the fall detection rate for the different number of hidden states and it specifies that the optimal number of the hidden states is two and it corresponds to fall detection rate 86.84%.The value of parameter area under curve is AUC=0.8684. It indicates that our proposed method present interesting results, and which means that most fall incidents are correctly detected. Although some sequences of lying down are detected as human fall.

5. Comparison with Other Methods

In our test, we made a comparison with other methods presented in the state of the art in [17, 21]. The two different methods integrating spatial and temporal features are compared to evaluate the falls detection performances.

In [17], authors use a human shape and motion history to detect a fall, they compute a motion coefficient and compare its value to the correspondent thresholds. The inconvenient of this method is the manual choice of the threshold for each activity.

Table 2 presents the resulted tests of the method indicated in [17].

Table 2. Confusion matrix of the shape and motion history.

	Detected As fall	**Detected as not fall**
Falls	TP:15	FN:2
Non falls	FP:3	TN:21

Authors in [21] used a tri-axial accelerometer to describe the human motion. The extracted features are used to train a HMM with one hidden variable with discrete observations.

To compare the performance of our method and the others presented in the state of the art we will use the concept of accuracy that can be obtained by the following Equation:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

The accuracy can be also obtained from the area under curve of the roc curve.

Table 3. Performance comparison of the three methods.

Method	**Accuracy**
Rougier *et al*. [17]	83%
Tang *et al*. [21]	81%
Our method	86.84%

The comparison of the different methods using the two factors sensitivity and specificity in Table 3, demonstrates the superiority of our methods although there is still a misdetection of some sequences.

6. Conclusions and Future Works

In this paper, a new method for video fall detection using a coupled Hidden Markov Model was presented. The fall detection system starts by segmenting the input video to a set of frames. Then it generates the background which will be subtracted from each one of them in order to detect the moving human silhouette. To repair the resulted noisy image, our system uses some morphologic filter.

The proposed method uses a fusion of motion and static spatial-temporal features to detect fall. Our experiments showed that the CHMM model is effective and detects most human fall and presents superiority against other existing methods for fall detection.

One of the limitations of our method is that the tests are performed on a dataset where young person simulating fall. The problem is that the orderly’s motions are different from the young’s one. In our future work, we try to create a dataset regrouping a set of video of elderly daily activities such as walking, jogging, sitting down, lying down and even fall.

Our future works will also include extending the proposed method to recognize human behavior in complex scene which contains multiple foreground moving objects.

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Mabrouka Hagui is phd student at the National Engineering School of Sousse (university of Sousse-Tunisia) and member of research Lab LATIS (Laboratory of Advanced Technology and Intelligent Systems), team signals, images and documents.

Mohamed Mahjoub is an associate professor in Signal and Image processing at the National Engineering School of Sousse (university of Sousse - Tunisia) and member of research Lab LATIS (Laboratory of Advanced Technology and Intelligent Systems), team signals, images and documents. His research interests include dynamic bayesian network, computer vision, pattern recognition, HMM and data retrieval. He is a member of IEEE and his main results have been published in international journals and conferences.

Faycel ElAyeb received the Ph. D degree in 2012 from National School of Informatic Sciences (University of Manouba-Tunisia). He works currently as an Assistant Professor in Preparatory Institute for Engineering Studies of Monastir. His major research interests are in the field of image analysis and pattern recognition.