Vision-Based Fall Detection System for Improving Safety of Elderly People

Fouzi Harrou, Nabil Zerrouki, Ying Sun, and Amrane Houacine

Recognition of human movements is very useful for several applications, such as smart rooms, interactive virtual reality systems, human detection and environment modeling. The objective of this work focuses on the detection and classification of falls based on variations in human silhouette shape, a key challenge in computer vision. Falls are a major health concern, specifically for the elderly. In this study, the detection is achieved with a multivariate exponentially weighted moving average (MEWMA) monitoring scheme, which is effective in detecting falls because it is sensitive to small changes. Unfortunately, an MEWMA statistic fails to differentiate real falls from some fall-like gestures. To remedy this limitation, a classification stage based on a support vector machine (SVM) is applied on detected sequences. To validate this methodology, two fall detection datasets have been tested: the University of Rzeszow fall detection dataset (URFD) and the fall detection dataset (FDD). The results of the MEWMA-based SVM are compared with three other classifiers: neural network (NN), naïve Bayes and K-nearest neighbor (KNN). These results show the capability of the developed strategy to distinguish fall events, suggesting that it can raise an early alert in the fall incidents.

Falls by elderly people can cause serious injury or death if sufferers remain on the ground for too long. The falls detection field has recently received increasing attention especially due to the rapid growth of communication and video monitoring systems. Several studies showed that falls are the main cause of trauma for people with special needs like seniors. As reported by the World Health Organization in [1], 30% of the population over 65 years-old experiences at least one trauma due to falling per year. Furthermore, 47% of seniors who have fallen have lost their ability for autonomy [2].

During recent years, increased attention to fall detection has led to the development of several fall detection approaches [3], [4]. Some methods are generally based on information gathered by sensors like vibration and acceleration sensors [3], [4]. These methods use vibrations, sound, and human movements in fall detection [4]-[6]. However, these methods present several problems which limit their performance by increasing the rate of false detections. The acoustic sensors can be easily affected by noise. Furthermore, the detection using floor vibration sensors is limited only to surfaces equipped with sensors. The cost of the sensor installation on a large area of ground is very important, which makes these methods inappropriate in real life. Currently, small sensors are available and embedded in many daily devices such as in smartphones and smartwatches.

Other approaches focused on using information extracted from video sequences for fall detection [7]. These approaches have been proposed using a single camera, multiple cameras [8], omnidirectional ones [9] and stereo-pair cameras [10]. Indeed, a camera provides more information about the motion of the monitored person and attempts to extract important features from the video sequences to detect potential falls. In other words, the data collected by cameras are richer and more informative than standard sensors. In particular, vision-based fall detection can be useful inside hospital rooms and care facilities to detect falls and improve patient safety. Falls of patients in hospitals can lead to physical and emotional injuries, an extension of the period of stay, an increase in health care costs, and a demand for more hospital resources.

In this paper, we consider the fall detection issue as an anomaly detection problem and propose using the MEWMA monitoring scheme [11]. The advantage of using the MEWMA chart is twofold. First, the use of an MEWMA chart offers better sensitivity in detecting falls. Second, this monitoring scheme is easy to implement in real time due to its low-computational cost. Unfortunately, the MEWMA monitoring chart cannot separate real falls from some fall-like actions. This misclassification is due to the similarity between features of such gestures. To bypass this confusion, an SVM

The research reported in this publication was supported by funding from King Abdullah University of Science and Technology (KAUST), Office of Sponsored Research (OSR) under Award No: OSR-2015-CRG4-2582.

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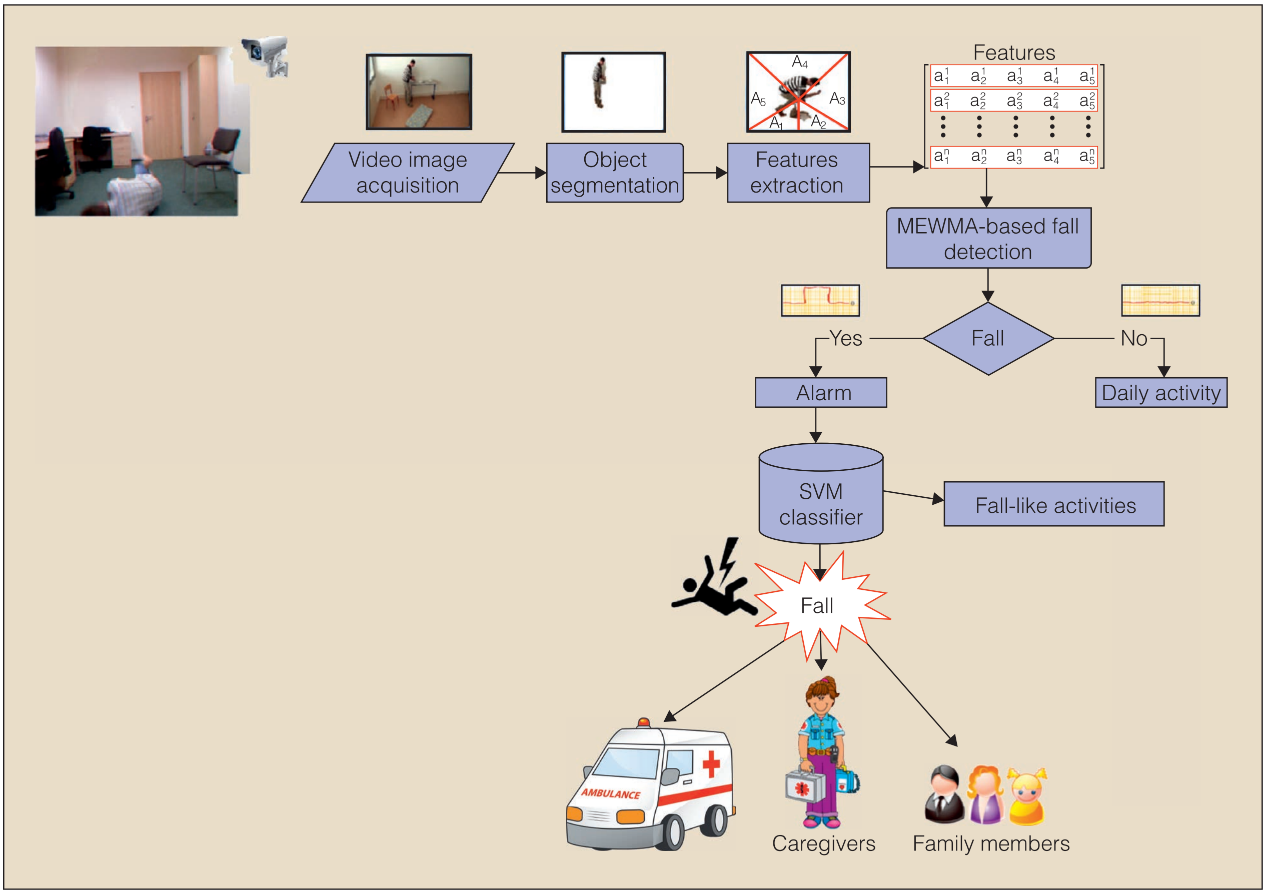

Fig. 1. Schematic of the proposed strategy.

algorithm is applied on detected cases to classify the type of fall and reduce the false alarm rate. The choice of SVM is motivated by its high performance and generalizability, since the SVM can be adjusted to perform as a linear or nonlinear algorithm by using nonlinear kernels. Of course, the combination of an MEWMA-SVM presents a high accuracy with a reduced computational time compared to that obtained via the conventional approaches.

The following sections present the vision based strategy, including human body extraction, image quality enhancement and feature generation. The paper reviews how anomaly detection is achieved by an MEWMA chart. Then, the SVM technique that distinguishes true falls from other fall-like actions is presented. We assess the performance of the developed approach. Finally, the paper concludes with a discussion and suggestions for future research directions.

A Vision-Based Fall Detection and Classification Strategy

The fall-detection procedure is implemented in five main stages: data acquisition, image segmentation, feature extraction, fall detection, and fall classification (Fig. 1).

The data acquisition module consists of acquiring frames or video sequences from the camera. The segmentation module extracts the body silhouette from the background. Feature extraction is central to video-based fall detection. It can be defined as the process by which important discriminative information is extracted from a segmented body.

Segmentation is applied using a background subtraction approach, as illustrated in Fig. 2. The background template and the input images are represented by Fig. 2a and Fig. 2b, respectively. Fig. 2c and Fig. 2d illustrate the segmentation results (before and after the application of morphological operators).

For the feature extraction phase, several characteristics have been used until now. However, most of them are highly dependent on the silhouette size and position. Body size changes when the distance from individuals to camera varies. A scaling operation with a distance factor is frequently used, but this operation requires a prior camera calibration. For that reason, we propose the use of five areas constituting the human body. These areas are obtained by defining five lines from the silhouette's center of gravity (Fig. 3). The first line is vertical, and two other lines are situated at 45° on each side from the first line, where the remaining segments are then traced at 100° on each side of the two latter lines. Then, we normalize each area's value by dividing its value by the whole area. Since video is assimilated to a sequence of frames, the area ratios extracted from the area ratios corresponding to each image are concatenated to constitute the whole vector.

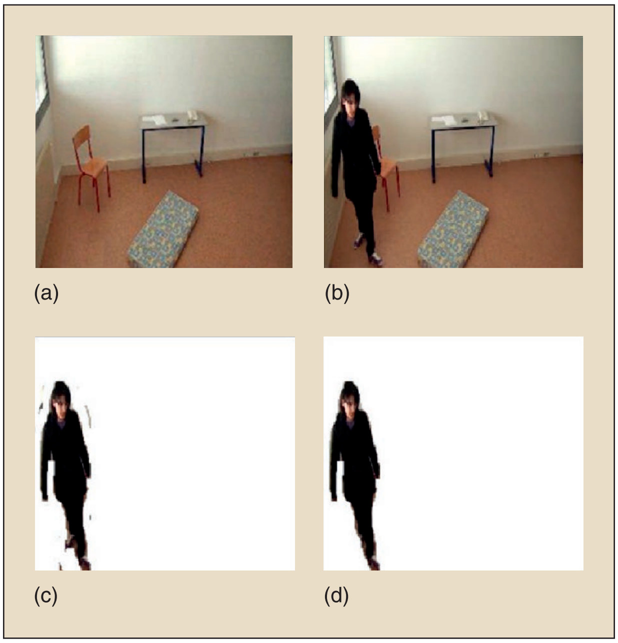

Fig. 2. An example of background subtraction procedure.

A MEWMA-Based Fall Detection Strategy

An MEWMA chart has been widely used to monitor industrial processes for many years [12]. This chart takes the correlations between variables into account and monitors a set of cross-correlated variables simultaneously. An MEWMA chart is able to detect small shifts, since the MEWMA statistic is a time-weighted average of all previous observations [12]. Let $\mathbf{X}_t = (\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_m)^T$ be a dataset obtained from a p-dimensional process. Herein, p represents the number of ratios that are computed for each image (i.e., p = 5). The MEWMA charting statistic is computed at each observation time point as follows [11]:

$$\begin{cases} \mathbf{Z}_t = \Lambda \mathbf{X}_t + \left(\mathbf{I}_{m\times m} - \Lambda\right)\mathbf{Z}_{t-1} & \text{if } t > 0 \\ \mathbf{Z}_0 = \mu_0, & \text{if } t = 0 \end{cases} \tag{1}$$

where $\Lambda = \text{diag}(\lambda 1, \lambda 2, \ldots, \lambda m)$ and $\lambda j \in (0,1]$ is a smoothing index or weight factor for the j-th component of $\mathbf{X}$, for $j = 1, 2, \ldots, m$, and $\mathbf{I}_{m\times m}$ denotes the identity matrix. We can see that if λ is small, then more weight is assigned to past observations. Thus, the chart is tuned to efficiently detect small changes in the process mean. Moreover, if λ is large, then more weight is assigned to the current observations, and the chart is more suitable for detecting large shifts [12]. The MEWMA monitoring statistic is:

$$\mathbf{V}_t^2 = \mathbf{Z}_t^T \Sigma_{Z_t}^{-1} \mathbf{Z}_t, \tag{2}$$

where Σ_{Z_t} is the covariance matrix of $\mathbf{Z}_t$. Then, the MEWMA chart with the charting statistic V_t^2 gives a signal of mean shift in cases when $\mathbf{V}_t^2$ overpasses a decision threshold h. The threshold h can be determined via simulation for a given probability of false alarm [12].

We note that it is often the case that an anomaly detector such as the MEWMA chart can detect anomalies but cannot distinguish detected anomalies from one another. Specifically, one disadvantage of the MEWMA anomaly detector is the lack of ability to discriminate the detected fall from false falls (i.e., fall-like). In this paper, falls classification based on the SVM algorithm is further developed to resolve this dilemma.

SVM-Based Fall Classification

The SVM formalism was initially proposed by Vapnik [13] and has been widely exploited in the fields of classification and detection. The principle of the SVM is to transform the feature's space into a higher dimensional space using a kernel function. This transformation allows approximately linear data to be

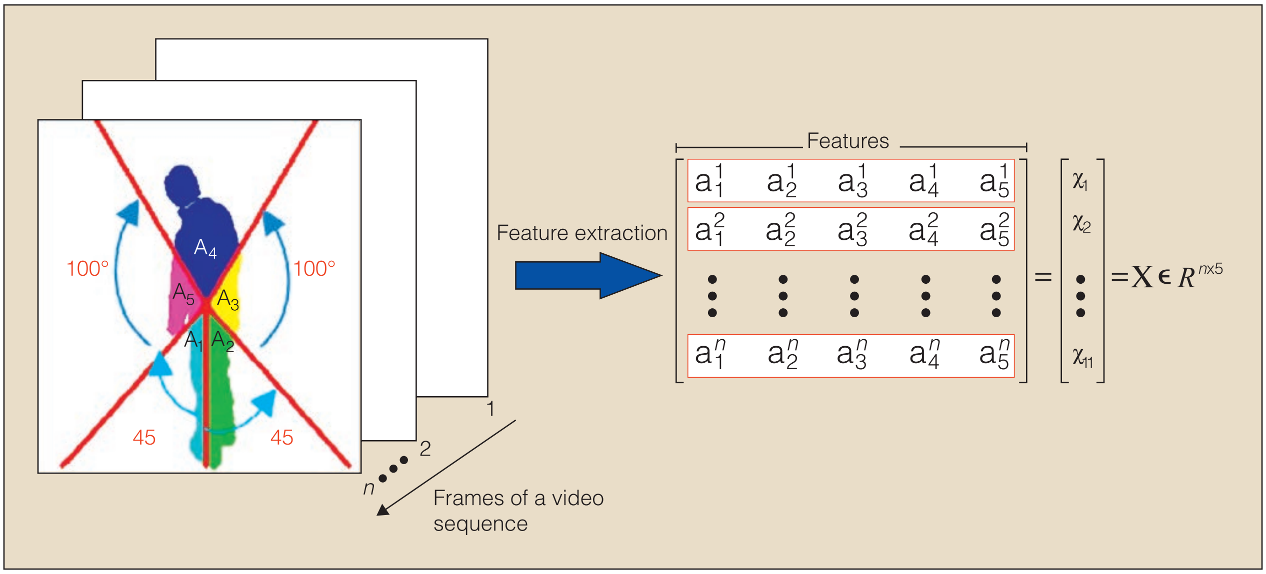

Fig. 3. Extracted features used as input for fall detection.

obtained and then defines the optimal separating hyper plane in the transformed space to classify different samples [13]. In the present application, SVM algorithm was selected as the classifier since it could be considered as a linear or nonlinear classifier by the use of nonlinear kernels. Different kernel functions can be chosen during the classification process. In this work three kernels were tested, namely: linear, polynomial, and radial basis function (RBF).

- Linear: $K(x_i , x_j) = x_i . x_j$
- Polynomial: $K(x_i , x_j) = (x_i . x_j + 1)^d$, where d is the degree of polynomial kernel.
- RBF: $K(x_i , x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)$, where σ is the width of Gaussian kernel.

In this work, SVM is applied to define the optimal separating hyperplane to classify detected sequences $y_k \in \{-1, +1\}$ into true falls and false falls, respectively. To assess the effectiveness of the proposed approach, a three-fold cross validation procedure is performed during classification, different statistical measures were computed, and one can cite the overall accuracy, F-measure, and the area under Receiver Operating Characteristic (ROC) [14].

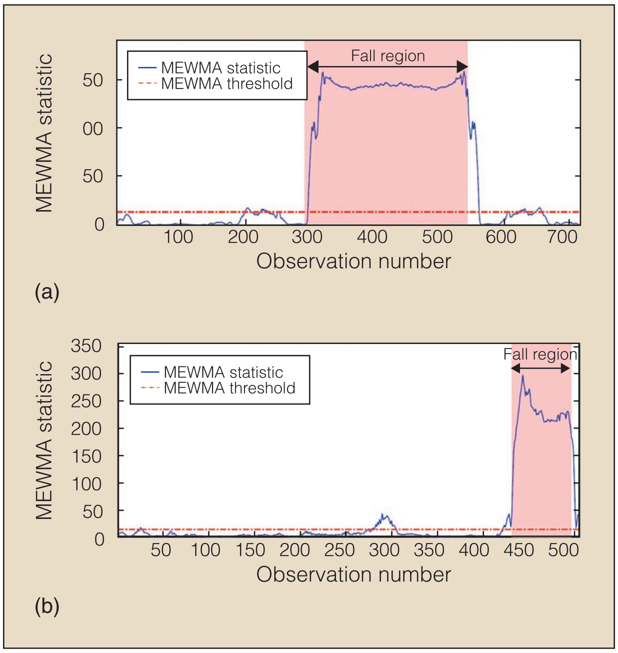

Fig. 4. Results of MEWMA chart in the presence of a fall (a) first example, (b) second example.

Experiments and Results

Data Description

The effectiveness of the developed strategy is validated using experimental data from two publically available databases: University of Rzeszow fall detection dataset (URFD) [15] and the fall detection dataset (FDD) [16]. URFD consists of 70 videos with various actions performed in different ways. All sequences representing falls and normal activities have been recorded with RGB cameras comprising 30 frames per video. The FDD includes 191 videos with a rate of 25 images/s and a resolution of 320 × 240 pixels. The proposed combination of MEWMA-SVM is evaluated and compared with some powerful algorithms namely: K-nearest neighbor (KNN), neural network (NN), and finally naïve Bayes classifier.

To quantify the efficiency of the MEWMA chart, two metrics have been used: the false detection rate (FAR) and the miss detection rate (MDR). The FAR is the number of normal observations that are wrongly judged as anomalies (false alarms) over the total number of anomaly-free data. The MDR is the number of anomalies that are wrongly classified as normal (missed detections) over the total number of anomalies. The smaller the FAR and MDR are, the better the detection rate is.

The MEWMA monitoring chart is first performed through the fall-free training data. We selected a set of 300 sub-videos as the fall-free training data from only ordinary activity sequences. The features or descriptors extracted from the fall-free training data were arranged as a matrix $\mathbf{X}$ having 300 rows (number of frames) and five columns (five area ratios extracted from the posture of each image). These data were first scaled (to have a zero mean and a unit variance) and then utilized to train the MEWMA chart. When the MEWMA monitoring chart is applied using the fall-free data, the MEWMA threshold value is found to be h = 13.82 for a false alarm probability of $\alpha = 5\%$ and $\lambda = 0.2$.

Detection Results

Firstly, the human body has been segmented and the area ratios have been extracted from the posture in the image. We studied two fall cases. In the first case, the testing sequence is tagged as a real fall (Case A), whereas the second sequence is tagged as a false fall (like a fast lying) (Case B).

Case A: True fall: Two examples are demonstrated in this section to illustrate the ability of the MEWMA scheme to identify fall events. In the first example, a fall occurred between frames 290 and 540 of the testing data. For the design of the MEWMA scheme, we chose $\lambda = 0.2$ and threshold $h = 13.82$. Fig. 4a shows that MEWMA detected the fall event with some false alarms and missed detection (FAR=7.54% and MDR=2%). In the second example, an MEWMA scheme with $\lambda = 0.2$ is applied to testing data with a fall between frame number 430 and 495. Fig. 4b shows the MEWMA statistic clearly exceeds the control limit, indicating the occurrence of an abnormal event. The MEWMA chart detects this fall event but with some false alarms (i.e., FAR=11.16%).

Case B: False fall– lying down: In the second case study, lying down occurred between frames 180 and 500 of the testing data. Fig. 5 illustrates results of the MEWMA detection. Several fall sequences are successfully detected, however there are some fall-like activities that were considered as falls. These confusions caused several false alarms in the detection system.

We note that the MEWMA chart cannot discriminate real falls from fall-like actions such as lying down quickly. To

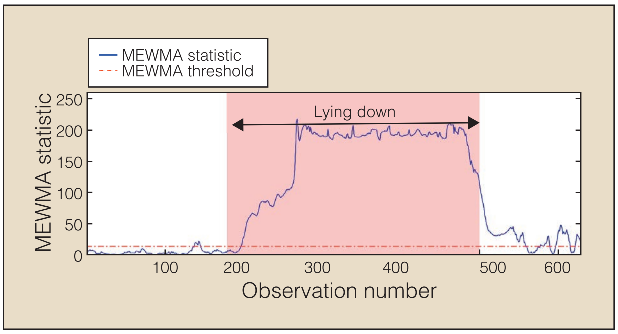

Fig. 5. Results of the MEWMA chart in the presence of a false fall (Case B).

bypass this shortcoming, a classification phase should be included after fall detection.

Classification Results

Data Description: To assess the performance of the SVM classification, we selected only those sequences that were previously identified as falls (during the MEWMA detection stage). The sequences should be classified into one of the two classes, namely true falls and false falls. These video samples were then split into training and testing sets. A three-fold cross validation procedure was used in this experiment.

Experimental Results: Table 1 compares the combined MEWMA fall detector and SVM classifier (MEWMA-SVM) with some well-known classifiers: KNN [15], neural network (NN) [16], and naïve Bayes, without the detection step. It is worth noting that the classifier's parameters have an important impact on the classification accuracy. Therefore, optimal parameters have been selected for each classifier, corresponding to the highest accuracy. In the case of NN, we selected a Multi-layer Perceptron (MLP) network with a back propagation (BP) learning algorithm consisting of one hidden layer with fifteen neurons. For KNN classification, the number of neighbors, k, has been varied from 1 to 20 to determine the optimal value. The value of k providing the highest accuracy is 3. For the SVM classifier [17], different SVM-kernel parameters, namely σ and cost C, were iteratively tested where σ is the width of Gaussian kernel and C is the parameter for the soft margin cost function. The pair providing the highest accuracy was selected ($\sigma = 0.125$ and $C = 128$).

Results shown in Table 1 testify that the MEWMA-SVM technique is more accurate than methods based only on classification alone. This fact is due to integration in the MEWMA detection phase, which separates daily activities from falling activities and thus reduces the number of sequences that will be used in SVM classification. Another reason that the MEWMA-SVM outperformed the neural network is that SVMs have a simple geometric representation and provide a sparse solution via structural risk minimization, while neural networks use empirical risk minimization. MEWMA-SVM outperformed KNN because of the capacity of SVM to train significant datasets, compared to the difficulty of KNN in searching nearest neighbors for all frames. The MEWMA-SVM technique has also shown better performance than the naïve Bayes classifier. This is relative to the independence assumption which is generally inappropriate in real world data. Furthermore, only detected sequences are classified by SVM, so just a part of videos is concerned with the classification task, which makes the processing much faster.

As shown in Table 1 (columns 9 and 10), the average training and testing times are calculated. The execution time is a significant tool to compare the complexity of algorithms. Neural network needs the longest training time to tune the parameters, while MEWMA-SVM obtains the shortest processing time. However, compared to KNN, naïve Bayes and NN present a reduced testing time. It is important to note that the MEWMA-SVM combination remains significantly better, since it presents the highest accuracy and an acceptable processing time.

We also compared the proposed approach with existing techniques applied to FDD and URFD datasets (Tables 2 and 3). Tables 2 and 3 illustrate a comparison between well-known classifiers namely: KNN, SVM, NN, variable-length particle swarm optimization (VPSO) neural network [18], and a directed acyclic graph SVM (DAGSVM) [2]. Results show that the MEWMA-SVM method outperformed other fall detection approaches and exhibited the highest accuracy. The main reason for the superiority of the MEWMA-SVM fall detection method lies in the fact that the former uses the MEWMA chart, which is well reputed by its high sensitivity to anomalies. Instead the detection phase used in [19], where the decision is based on thresholds, is fixed manually. This superiority confirms also the advantage of the use of pixels-based area ratios which helped to a significant description of human body. Due to the translation and scaling invariant, their application is adapted to all video sequence types, and no prior camera calibration is required. Of course, based upon the results of the experiments carried out, the new method that applies

Table 1 – Comparison between MEWMA-SVM and four commonly used classifiers

Classifier	Accuracy	Se	Sp	Precision	Recall	F-measure	AUC	Training time	Testing time
KNN	91.94	1	0.86	0.838	1	0.91	0.93	0.28	
Neural Network	95.15	1	0.91	0.903	1	0.95	0.95	2.65	0.15
Naïve-Bayes	93.55	1	0.886	0.87	1	0.93	0.94	0.61	0.26
MEWMA-SVM	96.66	1	0.9493	0.9355	1	0.9524	0.9526	0.212	0.0357

Table 2 – Comparison of different fall detection procedures using URFD database		
	Approach	Overall accuracy (%)
Kwolek and Kepski [17]	SVM	90.00
Kwolek and Kepski [15]	SVM	94.28
	KNN	95.71
The proposed approach	MEWMA-SVM	96.66

Table 3 – Comparison of different fall detection procedures using FDD database		
	Approach	Overall accuracy (%)
L. Alhimale *et al.* [19]	Neural Network	94.27
X. Ma *et al.* [18]	VPSO-Neural Network	92.17
M. Yu *et al.* [2]	DAGSVM	96.09
The proposed approach	MEWMA-SVM	97.02

MEWMA-SVM seems to offer a more suitable fall detection capability than existing approaches.

Results recommend that the features corresponding to detected falls help to improve the performance of true/false fall classification. Furthermore, the MEWMA monitoring has a central role in reducing the size of the features utilized as input data to SVM for classification. We also compared MEWMA-based SVM with SVM without the detection phase, NN, KNN and naïve Bayes classifiers. The comparative results show the superior classification capability of MEWMA-based SVM compared with other classifiers. There were several reasons that the SVM outperformed NN. Importantly, we found that the proposed features, detector and classifier are capable to detect and distinguish the type of fall with a higher accuracy compared to current techniques. Of course, the results demonstrate that the MEWMA-based SVM improves fall classification.

Currently, many small sensors are available with the option to be embedded in many daily devices such as smartphones and smartwatches, allowing free body movement for the elderly. In future work, we plan to incorporate information from accelerometers or gyroscopes with camera-based approaches to improve further the detection accuracy. Moreover, we plan to incorporate more data inputs such as heart rate and blood pressure provided by a smartwatch or a smartphone to further enhance the effectiveness of a fall detection system.

Acknowledgment

The authors (Nabil Zerrouki and Amrane Houacine) would like to thank the LCPTS Laboratory, Faculty of Electronics and Informatics at the University of Sciences and Technology Houari Boumédiene (USTHB) for the continued support during the research. We would like to thank the reviewers of this article for their insightful comments, which helped us to greatly improve its quality.

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