# An Eigenspace-Based Approach for Human Fall Detection Using Integrated Time Motion Image and Multi-class Support Vector Machine

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## Abstract

*Falls are a major health hazard for the elderly and a serious obstacle for independent living. Since falling causes dramatic physical-psychological consequences, development of intelligent video surveillance systems is so important due to providing safe environments. To this end, this paper proposes a novel approach for human fall detection based on combination of integrated time motion images and eigenspace technique. Integrated Time Motion Image (ITMI) is a type of spatio-temporal database that includes motion and time of motion occurrence. Applying eigenspace technique to ITMIs leads in extracting eigen-motion and finally multi-class Support Vector Machine is used for precise classification of motions and determination of a fall event. Unlike existent fall detection systems that only deal with limited movement patterns, we considered wide range of motions consisting of normal daily life activities, abnormal behaviors and also unusual events. Reliable recognition rate of experimental results underlines satisfactory performance of our system.*

## 1. Introduction

Fall in the elderly is a major public health problem as it causes many disabling fractures but also has dramatic psychological consequences that reduce the independence of the person. It was established that the earlier the fall is reported, the lower is the rate of morbidity-morality[1]. The elderly are prone to accidental falls causing serious injuries and it is known that falls are the leading cause of injury deaths among individuals who are high years old[2]. Thus with the population growing older and increasing number of people living alone, supportive home environments able to automatically monitor human activities are likely to widespread due to their promising ability of helping elderly people. Recently more researches focus on the detection of fall accident for the elderly, current solutions to detect falls can be categorized as follows [1], [3]:

- Sensitive Floor Tiles: These tiles are installed in all places. The main problem is that the falls which do not end on the ground or which occur in locations that aren't occupied with the specialized tiles are obviously not detectable.
- Simple Sensors (like Passive Infrared Sensors): They provide fairly crude data that's difficult to interpret.
- Wearable Sensors (such as accelerometers or help buttons): These autonomous sensors are usually attached under the armpit, around the wrist, behind the ear's lobe, at the waist or even on the chest. These sensors have gyroscopes or accelerometers embedded in them and detect velocity or accelerate exceed a specific threshold, vertical posture toward lying posture, and also absence of movement after fall. However the problem of such detectors is that older people often forget to wear them, indeed their efficiency relies on the person's ability and willingness to wear them, moreover in the case of a help button, it can be useless if the person is unconscious or immobilized.
- Computer Vision Systems: These approaches try to extract some considerable features from video sequences of movement patterns to detect falls. Camera is usually placed sideways or on the ceiling.

In this paper we present a novel video analysis based approach for monitoring human activities with a particular interest to the problem of fall detection. The reminder of the paper is organized as follows: in section 2 we briefly review some existing vision-based fall detection systems, in section 3 our proposed system is described in more details. Experimental results are represented in section 4 and finally we

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conclude in section 5 and propose some directions for future work.

## 2. Related Work

Recently some research has been done to detect falls using image processing techniques. A simple method was used in [5], [6] based on analyzing aspect ratio of the moving object's bounding box. This method could be inaccurate, depending on the relative position of the person, camera, and perhaps occluding objects. The works in [2], [7] used the normalized vertical and horizontal projection of segmented object as feature vectors. To overcome occluding objects problem, some researchers have mounted the camera on the ceiling: Lee [8] detected a fall by analyzing the shape and 2D velocity of the person. Nait-Charif [9] tracked the person using an ellipse and inferring falling incident when target person is detected as inactive outside normal zones of inactivity like chairs or sofas. Rougier [4] used wall-mounted cameras to cover large areas and falls were detected using motion history image and human shape variation. Other systems used the audio information or using 3D trajectory and speed of head to infer events [11]. These mechanisms tend to be more complex and need more additional cost.

Despite the considerable achievements that has accomplished on this field in the recent years, there are still some challenges to overcome:

- Most of current systems [6], [7], [9], [10] are unable to differentiate between real fall incident and an event where the person is simply lying or even extracted features aren't sufficient to discriminate a real fall from a person sitting down abruptly. This mistake is made due to either inappropriate feature extraction or poor classification.
- Existent fall detection systems tend to deal with restricted range of movement patterns and fall incidents are usually detected in contrast with limited normal scenarios like walking; however in real home environments various normal and abnormal motions can occur.

To overcome these drawbacks in this paper we present a novel method, which aims not only to detect and record fall events, but also other postures in a home environment with a considerable recognition rate. The main characteristics of our system are:

- We tried to simulate real life situations; to this aim, we have considered comprehensive and various movement scenarios consisting *normal* daily life activities such as walking, running, bending down, sitting down and lying down, some *abnormal* behaviors like limping or stumbling, and also *unusual* events like falling. Furthermore several scenarios of falling have been regarded.
- In order to represent a human motion, we propose a new kind of integrated time motion image. Applying eigenspace technique to these representations describes each motion as a feature vector.
- This paper investigates the use of multi-class support vector machines for human posture recognition. We present three multi-class SVM techniques based on binary classifiers to improve recognition rate.

## 3. Proposed System Overview

Overview of system framework is shown in Fig.1

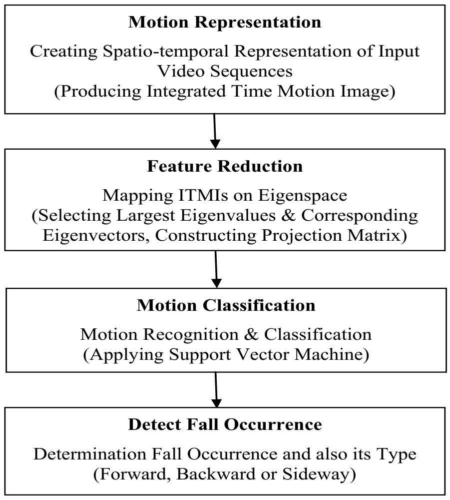



**Figure 1** Proposed System Flow

Since motion give crucial information about behavior and also we are interested in analyzing the motion occurring in a given window of time, we need a method that allows us to capture and represent motion directly from the video sequence. While existent static representations are functions of the observed motion parameters at the corresponding spatial information of the video sequence, in this paper we propose a spatio-temporal representation of video sequences. Based on Integrated Time Motion Image (ITMI) observation we extract some motion information from the video sequence. For extracting considerable features from these representations we selected eigenspace technique.

Among the most successful approaches used in face recognition we can mention eigenspace-based methods, which are mostly derived from the Eigenface algorithm. These methods project the input faces onto a dimensional reduced space where the recognition is carried out, performing a holistic analysis of the faces

[24]. In this paper like face recognition, we define eigen-motion in eigenspace and calculate them by using ITMIs. Then reduced feature vectors are used as input for the multi-class SVM classifier.

### 3.1. Preprocessing

In video databases, one of important methods for describing video scene is utilization of space and time relation between objects in the scene. In [17], [18], [21] conventional strategy for describing objects position is using two-dimensional coordinates. Increasing interval time feature for each changing of object in the scene and direction of movement is discussed in [19]. Stacking frame is presented in [20] for spatio-temporal knowledge representation. In this technique, few frames of one action are combined that result is type of temporal smoothing. Of course combination may be performed in gray-level or transformed domain. Also, spatio-smoothing using known image filters and adding consecutive frames is a type of spatio-temporal database which has been applied in lip reading for speech recognition [22].

In [23], MHI (Motion History Image) and MFH (Motion Flow History) are presented. MHI template includes time of occurrence of motion but direction of motion is not saved:

$$MHI(k,l) = \begin{cases} \tau & if \left|m_x^{kl}(\tau)\right| + \left|m_y^{kl}(\tau)\right| \neq 0 \\ 0 & Otherwise \end{cases} \quad (1)$$

Where $\tau$ is time of action occurrence and $(k,l)$ is position of occurrence in image. $m_x^{kl}(\tau)$, $m_y^{kl}(\tau)$ are component of motion vector in time of $\tau$ and position of $(k,l)$ in x,y directions respectively.

MFH includes position and direction of performing action as follows:

$$MFH_d(k,l) = \begin{cases} m_d^{kl}(\tau) & if\ E\left[m_d^{kl}(\tau)\right] < T \\ M\left(m_d^{kl}(\tau)\right) & Otherwise \end{cases} \quad (2)$$

Where

$$E\left[m_d^{kl}(\tau)\right] = \left\| m_d^{kl}(\tau) - med\left(m_d^{kl}(\tau), \ldots, m_d^{kl}(\tau-\alpha)\right)\right\| \quad (3)$$

$$M\left(m_d^{kl}(\tau)\right) = med\left(m_d^{kl}(\tau), \ldots, m_d^{kl}(\tau-\alpha)\right)$$

In the above equation, $\alpha$ is the number of old frames and set between 3 and 5.

MFH and MHI are complementary temporal templates because they include spatial, temporal and directional information. In the MHI, repeated motions in the same position in different times give similar result. This is a problem in storing occurrence time of action. In this paper, we propose a spatio-temporal representation include storing occurrence time of each motion with emphasizing at final action. Other dominant note in this paper is application of spatio-temporal database in human motion recognition. We define Integrated Time Motion Image at time t and location *(k,l)* as follows:

$$ITMI_t(k,l) = ITMI_{t-\Delta t}(k,l) + tf(t) \quad (4)$$

Where *f(t)* is:

$$f(t) = I(k,l,t) - I(k,l,t-\Delta t) \quad (5)$$

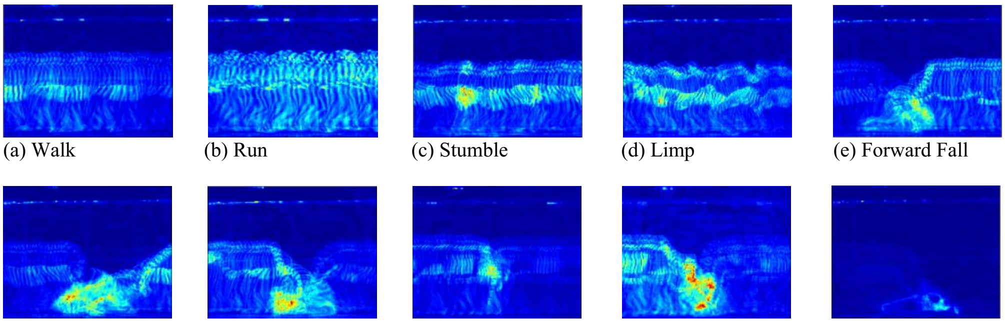
Where *I(k,l,t)* is the current image sequence and $\Delta t$ is a specific time interval. It's also proved that ITMI is robust against noise. ITMI represents the human action in a very compact manner. Given a set of ITMIs for each movement, we extract features from this motion history information for characterizing human actions. An Example of each motion is demonstrated in Figure 6, corresponding ITMIs are also presented in Figure2.

### 3.2. Feature Extraction

The eigenspace technique is one of linear dimensionality reduction techniques, and it has already been employed in object recognition, human face recognition, and so on. We use this technique for recognizing human motions. Eigenspace-based approaches approximate the behavior images with lower dimensional feature vectors. The main supposition behind this procedure is that the behavior space (given by the dimension of the feature vectors) has a lower dimension than the image space (given by the number of pixels in each image), and that the recognition of the behaviors can be performed in this reduced space. These approaches consider a training phase where the behavior database is created and the projection matrix is obtained from all the database behavior templates. In the training phase the reduced representations of each database behavior are also obtained. These representations are the ones to be used in the recognition process [16], [24].

Creating eigenspace is done as follows: Behavior templates of previous step are considered as input images of this step. Each ITMI is displayed by a vector $\Gamma$. So for $M$ learning samples we have $\{\Gamma_i \mid i = 1, \ldots, M\}$, average of these vectors is:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \quad (6)$$



(a) Walk (b) Run (c) Stumble (d) Limp (e) Forward Fall

(f) Backward Fall (g) Sideway Fall (h) Bend down (i) Sit down (j) Lie down

**Figure 2** ITMIs of Different Scenarios

Then difference of each sample with the mean image vector is calculated:

$$\Phi_i = \Gamma_i - \Psi, \quad i = 1, \ldots, M \tag{7}$$

Now we create a data matrix $A$ from a set of normalized learning image data $\Phi_i (i = 1 \ldots M)$

$$A = [\Phi_1, \ldots, \Phi_M] \tag{8}$$

Covariance matrix C is defined as follows:

$$C = AA^T \tag{9}$$

The eigenvalues and the corresponding eigenvectors of covariance matrix $C$ are obtained by solving the following eigen equation:

$$Cx = \lambda x \tag{10}$$

Eigenvectors of matrix $C$ are $v_i (i = 1, \ldots, M)$. An eigenspace is created from $L$ eigenvectors chosen corresponding to the largest $L$ eigenvalues out of $M$. selected eigenvectors construct matrix:

$$B = \{v_i \mid i = 1, \ldots, L\} \tag{11}$$

Length of each $v_i$ vector is $M$ and matrix dimensions are $M \times L$. Projection matrix is defined as:

$$P = AB \tag{12}$$

Now each input template is transferred to eigenspace by using projection matrix $P$. Equation 13 demonstrates that input template $I$, is multiplied by projection matrix after eliminating mean value $\Psi$ from it and would be transferred to eigenspace.

$$\Omega = P^T (I - \Psi) \tag{13}$$

Eigenvectors corresponding to largest eigenvalues - that represent more suitable information - are selected. These vectors are used as inputs of classifier. Notice that features reduction by PCA from 60 to 3, does not have any sensible effect on recognition rate. The point in which the area under curve of eigenvalues equals to 90% of total area of under curve is selected as reduced features number (3). Figure 5 shows three eigen-motions selected by PCA.

### 3.3. Human Motion Classification

Support vector machines (SVM) were originally designed for binary classification. How to effectively extend it for multi-class classification is still an on-going research issue. Currently there are two types of approaches for multi-class SVM. One is by constructing and combining several binary classifiers while the other is by directly considering all data in one optimization formulation. Since methods solving multi-class SVM in one step (All-Together Methods), much larger optimization problem is required; we focus on the methods based on binary classification: One Against All, One Against One and DAGSVM [12] - [14]

**1. One-Against-All Method**

One-against-all (OAA) method uses k binary SVMs to classify k classes. Each SVM is trained with train data to identify a class. In our research problem that distinguishes ten different postures, the structural diagram is as in Figure 3. The first SVM identifies ***Walk***. In order to distinguish class ***Walk*** from other classes ***Run, Stumble, Limp …. Lie down*** train data corresponding to ***Walk*** have +1 and the others have -1. Then, for test data, each SVM is given the same input data, and the output values from the SVMs are compared, and the data is identified as the class of the SVM that produced the largest output value.

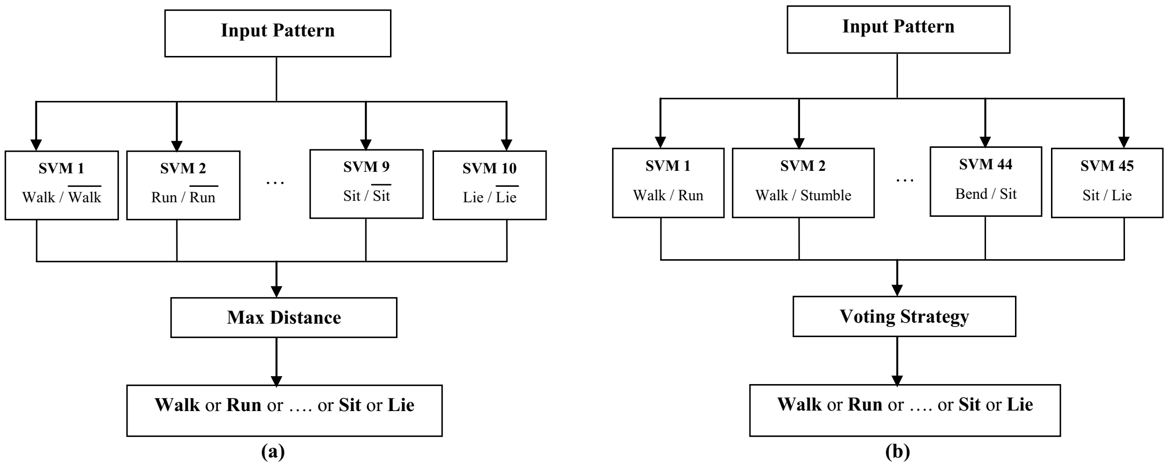



**Figure3** Structures of Multi-class SVM using (a) OAA and (b) OAO approaches

**2. One-Against-One Method**

Different from OAA, One-against-one (OAO) method uses k(k-1)/2 binary SVMs to identify k classes. Each train data is divided into two classes. For our research problem, the structural diagram is as in Figure 3. The first SVM has train data composed of class ***Walk*** and class ***Run***, and it also classifies only class ***Walk*** and class ***Run*** in test data. When classifying test data, all of the SVMs perform classification and test data is identified as the class with the largest number of votes. The voting approach is also called “Max Win” strategy.

**3. Direct Acyclic Graph SVM**

Its training phase is the same as the OAO method by solving k(k-1)/2 binary SVMs. However, in the testing phase it uses a rooted binary directed acyclic graph which has k(k-1)/2 internal nodes and k leaves. Each node is a binary SVM of *i*th and *j*th classes. Given a test sample *x*, staring at the root node, the binary decision function is evaluated. Then it moves to either left or right depending on the output value. Therefore, we go through a path before reaching the leaf node which indicates the predicted class. The structural diagram is presented at Figure 4.

Our experiments indicate that OAO and DAG methods are more suitable for practical use, and this is probably because of characteristic of intended SVM for binary classification. Besides we used different kernel functions dot, polynomial and RBF (Radial Basis function) and best results obtained using RBF kernel. All available data are random divided into two subsets, for training and testing respectively. Table 2 represents best results obtained using OAO method and RBF kernel function.

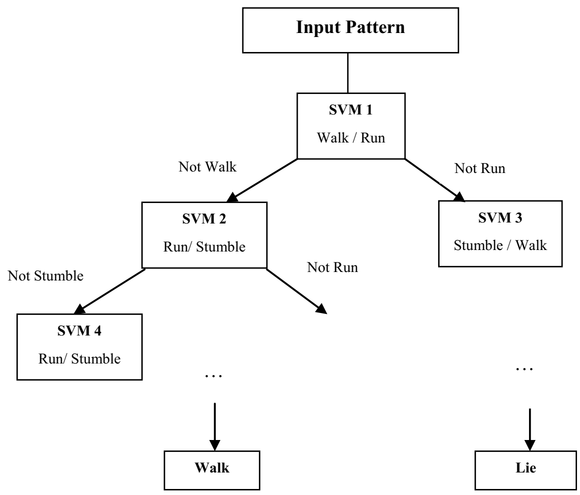



**Figure 4** Structure of Multi-class SVM using DAGSVM approach

## 4. Experimental Results

In order to validate the overall system performance we applied the proposed approach to a set of videos recorded in our lab. Here we consider indoor environment settings with single fixed camera monitoring static scene. Distance of person to the camera is approximately 4-5 meters. We assume a point of view where human posture is easily recognizable without ambiguities. From the security point of view, we could expect three different kinds of behavior: Normal, Unusual and Abnormal.

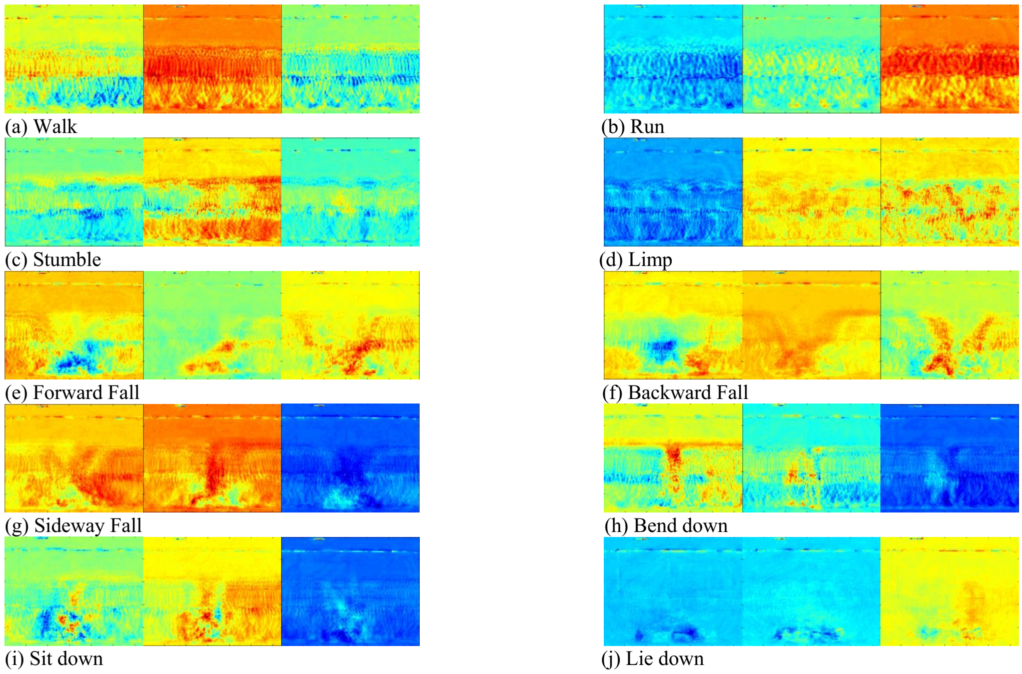



**Figure 5** Reduced Eigen-motions by PCA

### a) Normal

**Daily Activity**: Five different normal daily activities have been considered: Walking with normal speed for few meters, Running or fast walking, Bending down for catching something on the floor and then rising up, Sitting down on the floor and then standing up and Lying down on the floor.

### b) Unusual

**Fall:** Although the scenarios of falling are very various, we can categorize them in three classes. Detection of various types of falls is valuable in clinical studies to determine fall incidence and costs associated with the treatment of fall injuries. Falls that do not require medical treatment often go underreported but are still very important in order to implement appropriate fall prevention guidelines.

As most falls occur during intentional movements initiated by the person, they happen mainly in forward or backward: stumbling on an obstacle during walking, backward slip on wet ground. If the person becomes unbalanced in the forward direction, he will try to take some steps forwards and probably projecting his arms for protection. If imbalance occurs backward, the person will try to sit down to possibly attenuate the intensity of the shock impact. But in some cases the fall occurs sideways, either during a badly controlled sit to stand transfer. In this case, the person frequently tries to grip the wall [1].

### c) Abnormal

**Stumble**: Subjects were asked to walk in an unusual way, e.g. as if they were suffering a balance deficiency such as dizziness. In these situations person is unable to keep his balance or symmetry and synchrony of his movement. Body movements suggest the person is in a dubious condition.

**Limp**: Limping may be caused by unequal leg lengths, experiencing pain when walking, muscle weakness, disorders of proprioception, or stiffness of joints. Someone taking a step with a limp appears to begin to kneel and then quickly rise up on the other leg; to bystanders the process may appear arduous and painful.

These different scenarios are represented in Table 1; also Figure 6 shows one example of each motion. The dataset has been collected along two weeks, by considering different light and weather conditions. 24 subjects with different height, weight and genders whose ages ranged from 20 to 30 were asked to participate in the project. We repeated 10 kinds of activities by 5 times in the experimental space and finally 50 video clips (320*240) were captured for each person with AVI format (30 fps). The experimental results show that the system has a robust recognition rate in detecting occurrence of considered events.

**Table 1** Different Scenarios

| Name | Description |
|---|---|
| Walk | Walking naturally a few meters |
| Run | Jogging or fast walking |
| Stumble | Unable to keep balance or symmetric and synchrony of movement |
| Limp | Suffering from gait abnormality |
| Forward Fall | Forward fall on knees, chest or arms |
| Backward Fall | Backward fall caused by slipping |
| Sideway Fall | Lateral fall to right or left on legs |
| Bend down | Bending down, catching something on the floor and then rising up |
| Sit down | Sitting down and then standing up |
| Lie down | Lying down on the floor |

Table 2 represents the experimental results. $N_a$ refers to number of actions. $N_c$ is number of correctly detected events, $N_f$ is number of falsely detected events and $R$ is the recognition rate.

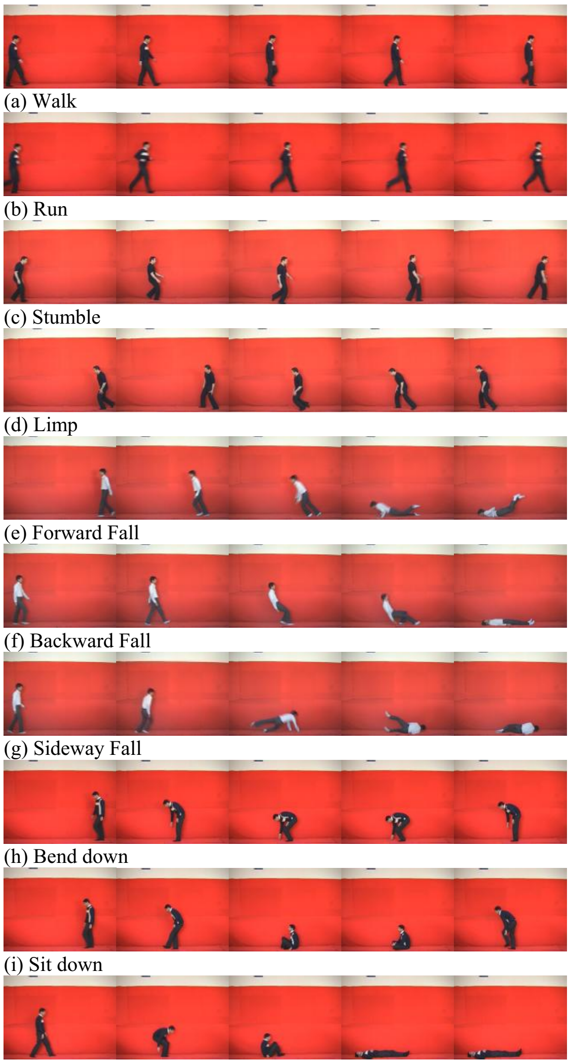
**Table 2** Recognition Rate for Various Events

| Events | $N_a$ | $N_c$ | $N_f$ | $R$ |
|---|---|---|---|---|
| Walk | 120 | 110 | 10 | 91.66 |
| Run | 120 | 105 | 15 | 87.50 |
| Stumble | 120 | 104 | 16 | 86.66 |
| Limp | 120 | 100 | 20 | 83.33 |
| Forward Fall | 120 | 109 | 11 | 90.83 |
| Backward Fall | 120 | 111 | 9 | 92.50 |
| Sideway Fall | 120 | 107 | 13 | 89.16 |
| Bend down | 120 | 105 | 15 | 87.50 |
| Sit down | 120 | 108 | 12 | 90.00 |
| Lie down | 120 | 115 | 5 | 95.83 |

## 5. Conclusions and Future Work

In this paper a novel efficient approach for activity recognition, principally dedicated to fall detection is proposed. The combination of motion and eigenspace technique, gives crucial information on human activities. Our experiments indicate that multi-class SVM methods are more suitable for human motion recognition than the other methods because of their capacity to solve an optimization problem in one step.

Our fall detection system has proven its robustness on realistic image sequences of ten different normal, abnormal and unusual human movement patterns. Reliable average recognition rate of experimental results (89.49%) underlines satisfactory performance and efficiency of our system.



(a) Walk (b) Run (c) Stumble (d) Limp (e) Forward Fall (f) Backward Fall (g) Sideway Fall (h) Bend down (i) Sit down (j) Lie down

**Figure 6** Examples of Each Motion

We claim that the developed system has the following distinctive features compared to existent fall detection systems:

- One of the main advantages of the proposed system in comparison with other human fall detection systems; is that we have considered wide range of motions, consisting normal daily life movements, some abnormal behaviors and also unusual events. While existent systems deal with limited movement patterns, we tried to simulate real life situations by considering wide variety of different postures. So the proposed system is not just an ordinary human fall detection system, it has many applicable properties and can be employed in different surveillance systems in houses, hospitals, schools and so on. Moreover while existing fall detection systems are only able to detect occurrence of fall behavior, the proposed system is able to detect type of fall incident (forward, backward or sideway).

- Multi-class SVM classification system reduced the false detection rate. According to the results, classification was more precise in multiclass SVM using OAO method than in that using OAA method.

Future works will include the incorporation of multiple elderly monitoring which is able to monitor more than one person in the scene and also be able to handle occlusion. Using additional features is also a subject to be explored in the future work. Although the eigenspace has thus far proven to be a useful method for feature extraction and reduction; additional features may be necessary or useful.

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