# X-Factor HMMs for detecting falls in the absence of fall-specific training data

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**Abstract.** Detection of falls is very important from a health and safety perspective. However, falls occur rarely and infrequently, which leads to either limited or no training data and thus can severely impair the performance of supervised activity recognition algorithms. In this paper, we address the problem of identification of falls in the absence of training data for falls, but with abundant training data for normal activities. We propose two 'X-Factor' Hidden Markov Model (XHMMs) approaches that are like normal HMMs, but have "inflated" output covariances (observation models), which can be estimated using cross-validation on the set of 'outliers' in the normal data that serve as proxies for the (unseen) fall data. This allows the XHMMs to be learned from only normal activity data. We tested the proposed XHMM approaches on two real activity recognition datasets that show high detection rates for falls in the absence of training data.

**Keywords:** Fall Detection, Hidden Markov Models, X-Factor, Outlier Detection

## 1 Introduction

Detection of falls is important because it can have direct implications on the health and safety of an individual. However, falls occurs rarely, infrequently and unexpectedly w.r.t. other normal Activities of Daily Living (ADL) and this leads to either little or no training data [9], which makes it very difficult to learn generalized fall detection classifiers due to the skewed class distributions. A typical supervised activity recognition system may not be very useful as a fall may not have occurred earlier. An alternative strategy is to build fall detection specific classifiers [5] that assume sufficient training data for falls, which is hard to obtain in practice. Another challenge is the data collection for falls, as it may require a person to actually undergo falling which may be harmful, ethically questionable, and cumbersome. The research question we address in this paper is: *Can we recognise falls by observing only normal ADL with no training data for the falls in a person independent manner?* To tackle this problem, we present two Hidden Markov model (HMM) based sequence classification approaches for detecting short-term fall events. The first method models individual activities by separate HMMs and an alternative HMM is constructed whose model parameters are averages of normal activity models, while the averaged covariance matrix is artificially "inflated" to model falls. In the second method, all the normal activities are grouped together and modelled with a common HMM and an alternative HMM is constructed to model falls with a covariance matrix "inflated" w.r.t the normal model. The inflation parameters of the proposed approaches are estimated using a novel cross-validation approach in which the outliers in the normal data are used as proxies for the (unseen) fall data.

In Section 2, we discuss the related research work, and the proposed HMM based approaches for fall detection in Section 3 and 4. Experimental results are presented in Section 5, followed by conclusions in Section 6.

## 2 Related Work

Several research works in fall detection are based on thresholding techniques [2], wherein raw or transformed sensor data is compared against a single or multiple pre-defined thresholds. A two-layer HMM approach, *SensFall* [13], is used to identify falls from other normal activities. In the first layer, the HMM classifies an unknown activity as normal vertical activity or "other", while in second stage the "other" activity is classified as either normal horizontal activity or as a fall. Chen et al. [4] present a fall detection algorithm that uses accelerometer data from a smartphone. A HMM is employed to filter out noisy data, One-class Support Vector Machines (OSVM) is applied to reduce false positives, followed by a posture analysis to reduce false negatives. Honda et al. [8] present an approach detecting nearly fall incidents of pedestrians in outdoor situations. They use Wii and Wii motion plus sensors and collected data for both normal activities and nearly fall incidents and use a SVM classifier for their identification. Zhang et al. [25] trained an OSVM from positive samples (falls) and outliers (non-fall ADL) and show that falls can be detected effectively. Yu et al. [24] propose to train Fuzzy OSVM on fall activity captured using video cameras and tuned parameters using both fall and non-fall activities. Their method assigns fuzzy membership to different training samples to reflect their importance during classification and is shown to perform better than OSVM. Shi et al. [19] use standard HMMs to model several normal activities including falls and perform classification with high accuracy from inertial sensors. Tong et al. [22] uses the accelerometer time series from human fall sequences and a HMM is trained on events just before the collision for early fall prediction. They also compute two thresholds for fall prediction and detection to tune the accuracy. Thome et al. [20] present a Hierarchical HMM (HHMM) approach for fall detection in video sequences. The HHMM's first layer has two states, an upright standing pose and lying. They study the relationship between angles in the 3D world and their projection onto the image plane and derive an error angle introduced by the image formation process for a standing posture. Based on this information, they differentiate other poses as 'non-standing' and thus falls can be identified from other motions.

The research works mentioned above assume that sufficient 'fall' data is available for training, which is hard to obtain in practice. Learning with few 'fall' samples has the disadvantage that it can underfit the results and may not produce generalized classifiers that work across people. To overcome the need for a sufficient set of representative 'fall' samples while learning, we propose two 'X-Factor' HMM based approaches that can identify falls across different people while learning only on data from normal activities.

## 3 Proposed Fall Detection Approaches

### 3.1 Threshold Based Detection – $HMM1_{out}$ and $HMM2_{out}$

The traditional way to detect unseen abnormal activities is to model each normal activity using an HMM, compare the likelihood of a test sequence with each of the trained models and if it is below a pre-defined threshold then identify it as an anomalous activity (we call this method as $HMM1_{out}$) [12, 21]. In respect to fall detection, this method can be described as follows: Each normal activity $i$ is independently modelled by an ergodic HMM which evolves through a number of $k$ states. The observations $o_j(t)$ in state $j$ are modelled by a single Gaussian distribution. Each model $i$ is described by the set of parameters, $\lambda_i = \{\pi_i, A_i, (\mu_{ij}, \Sigma_{ij})\}$, where $\pi_i$ is the prior, $A_i$ is the transition matrix, and $\mu_{ij}$ and $\Sigma_{ij}$ are the mean and covariance matrix, respectively, of a single Gaussian distribution, $\mathcal{N}(\mu_{ij}, \Sigma_{ij})$, giving the observation probability $P(o_j|j)$ for the $j^{th}$ HMM state. The parameters, $\lambda_i$, of a given HMM are trained by the Baum-Welch (BW) algorithm [18]. This method estimates the probability that an observed sequence has been generated by each of the $n_i$ models of normal activities. If this probability falls below a (pre-defined) threshold $T_i$ for each HMM, a fall is detected ($HMM1_{out}$).

Another common method to detect anomalous activities is to model all the normal activities by a common HMM instead of modelling them separately. The idea is to learn the 'normal concept' from the labelled data itself. The parameters of this combined HMM are $\lambda_{normal} = \{\pi, A, (\mu_j, \Sigma_j)\}$. This method estimates the probability that the observed sequence has been generated by this common model and if this probability falls below a (pre-defined) threshold $T$, a fall is detected ($HMM2_{out}$) [10].

### 3.2 Approach I - (XHMM1)

The 'X-factor' approach [17] deals with unmodelled variation from the normal events that may not have been seen previously by inflating the system noise covariance of the normal dynamics to determine the regions with highest likelihood which are far away from normality based on which events can be classified as 'not normal'. We extend this idea by constructing an alternate HMM to model unseen fall activity, which has the same number of states as the other $n_i$ models for normal activities (each normal activity is modelled with same number of states). The parameters of this alternate HMM is obtained by averaging the parameters of $n_i$ HMMs and increasing the averaged covariances by a factor of $\xi$ such that each state's covariance matrix is expanded. Thus, the parameters of the X-Factor HMM will be $\lambda_{XHMM1} = \{\bar{\pi}, \bar{A}, \bar{\mu}, \xi\bar{\Sigma})\}$, where $\bar{\pi}$, $\bar{A}$, $\bar{\mu}$, and $\bar{\Sigma}$ are the average of the parameters $\pi_i$, $A_i$, $\mu_i$ and $\Sigma_i$ of each $n_i$ HMMs. The value of $\xi$ is computed using cross validation.

### 3.3 Approach II - (XHMM2)

Similar to $XHMM1$, an alternative HMM is constructed to model the unseen 'fall' activities ($XHMM2$) whose parameters remain the same as the HMM to model normal activities ($\lambda_{normal}$) except for the inflated covariance, and is given by, $\lambda_{XHMM2} = \{\pi, A, (\mu_j, \xi\Sigma_j)\}$. The parameter $\xi$ is computed using cross validation.

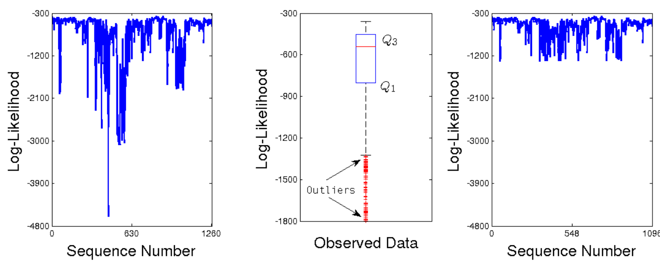
## 4 Threshold Selection and Proxy Outliers

Our goal is to train both the XHMMs and threshold based HMMs using only "normal" data (activity sequences that are not falls, see Figure 2). Typically, this is done by setting a threshold on the likelihood of the data given an HMM trained on this "normal" data. This threshold is normally chosen as the maximum of negative log-likelihood [10], and can be interpreted as a slider between raising false alarms or risking miss alarms [21]. However, any abnormal sensor reading or mislabelling of training data can alter this threshold and adversely effect the classification performance.

We propose to use outliers from the "normal" data to set thresholds. The idea is that, even though the "normal" data may not contain any falls, it will contain sensor readings that are spurious, incorrectly labelled or significantly different. These outliers can be used to set the thresholds that are required for fall detection, thereby serving as a proxy for the fall data in order to learn the parameters of the (X)HMMs. To find the outliers, we use the concept of quartiles from descriptive statistics. The quartiles of a ranked set of data values are the three points that divide the data set into four equal groups, where each group comprises of a quarter of the data. Given the log-likelihoods of sequences of training data for a HMM and the lower quartile ($Q_1$), the upper quartile ($Q_3$) and the inter-quartile range ($IQR = Q_3 - Q_1$), a point $P$ is qualified as an outlier if

$$P > Q_3 + w \times IQR \quad || \quad P < Q_1 - w \times IQR \tag{1}$$

where $w$ represents the percentage of data points that are within the non-extreme limits. Figure 1 (a) shows the log-likelihood $\log P(O|\lambda_{running})$ for 1262 equal length (1.28s) running activity sequences. Figure 1 (b) is a box plot showing the quartiles for this dataset, and the outliers (shown as +) for $w = 1.5$ (representing 99.3% coverage). Figure 1 (c) shows the same data as in (a) but with the outliers removed.




(a) (b) (c)

Fig. 1: Outlier removal using IQR on likelihoods

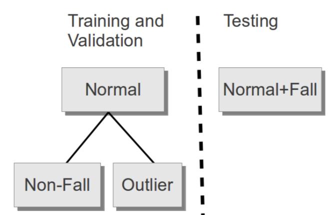



Fig. 2: Cross Validation Scheme

To train both the XHMMs/HMMs using only normal data, we first split the normal data into two sets: "non-fall" data and "outlier" data (see Figure 2). We do this using Equation 1 with a parameter $w = w_{CV}$ that is manually set and only used for this initial split. We train the HMMs on the "non-fall" data and then set the thresholds ($w$ (which is defined as $T_i$ for $HMM1_{out}$ and $T$ for $HMM2_{out}$) and $\xi$ for $XHMM1$ and $XHMM2$) by evaluating performance on the "outlier" data. We use a 3-fold cross validation: the HMMs are trained on $2/3^{rd}$ of the 'non-fall' data, and tested on $1/3^{rd}$ of the 'non-fall' data and on all the "outlier" data. This is repeated for different values of $w$ and $\xi$. The value of parameters that give the best averaged $gmean$ (see Table 4) over 3-folds are chosen as the best parameters. Then, each classifier is re-trained with these values on 'non-fall' activities.

# 5 Experimental Analysis

## 5.1 Dataset

The proposed fall detection approaches are evaluated on the following two datasets:

1. German Aerospace Center (DLR) [15]: This dataset is collected using an Inertial Measurement Unit with integrated accelerometer, gyroscope and 3D magnetometers with sampling frequency of 100 Hz. The dataset contains samples taken from 19 people under semi-natural conditions. The sensor was placed on the belt either on the right/left side of the body or in the right pocket in different orientations. The dataset

contains 7 activities: standing, sitting, lying, walking (up/downstairs, horizontal), running/jogging, jumping and falling.

2. MobiFall [23]: This dataset is collected using a Samsung Galaxy S3 device equipped with 3D accelerometer and gyroscope. The mobile device was placed in a trouser pocket in random orientations. Mean sampling of 87Hz is reported for accelerometer and 200Hz for the gyroscope. The dataset is collected from 11 subjects; eight normal activities are recorded in this dataset: step-in car, step-out car, jogging, jumping, sitting, standing, stairs (up and down joined together) and walking. Four different types of falls are recorded – forward lying, front knees lying, sideward lying and back sitting chair. Different types of falls are joined together for testing.

### 5.2 Data Pre-Processing

For the DLR dataset, accelerometer and gyroscope sensor readings are tilt compensated with the calibration matrix provided with the dataset. For MobiFall dataset, due to the difference in sampling rates, readings from the gyroscope were not used. Sensor noise is removed by using a Buttersworth low-pass filter with a cutoff frequency of 20Hz. The dataset is segmented with 50% overlapping windows, where each window size is 1.28 seconds to simulate a real-time scenario with fast response. To extract temporal dynamics for the XHHMs and HMMs, each window is sub-divided into 16ms frames and features are computed for each frame. Each activity in the XHHMs and HMMs is modelled with 4 states, and 5 representative sequences per activity are manually chosen to initialize the parameters. Initialization is done by segmenting a single sequence into 4 equal parts and computing $\mu_{ij}$ and $\Sigma_{ij}$ for each part and further smoothing by BW with 3 iterations. The transition Matrix $A_i$ is chosen such that transition probabilities from one state to another are 0.025, self-transitions are set accordingly. Four signals were extracted from the dataset (see Table 1) and 19 time and frequency-domain features are computed from them (see Table 2).

| **Name of Signal** | **Description** |
|---|---|
| Norm of acceleration | $a_{norm} = \sqrt{x^2 + y^2 + z^2}$ |
| Horizontal acceleration | $a_{horiz} = \sqrt{x^2 + y^2}$ |
| Vertical acceleration | $a_{vert} = z$ |
| Horizontal Angular velocity | $\omega_{horiz} = \sqrt{\omega_x^2 + \omega_y^2}$ |

Table 1: Different signals extracted from sensor readings.

| **#features** | **Type of feature** |
|---|---|
| 3 | Mean of $a_{norm}$, $a_{horiz}$, $a_{vert}$ |
| 3 | Max of absolute values of $a_{norm}$, $a_{horiz}$, $a_{vert}$ |
| 3 | Standard Deviation of of $a_{norm}$, $a_{horiz}$, $a_{vert}$ |
| 4 | IQR of $a_{norm}$, $a_{horiz}$, $a_{vert}$, $\omega_{horiz}$ |
| 1 | Normalized Average PSD of $a_{norm}$ |
| 1 | Spectral Entropy of $a_{norm}$ [6] |
| 1 | DC component after FFT of $a_{norm}$ [1] |
| 1 | Normalized Information Entropy of the Discrete FFT component magnitudes of $a_{norm}$ [1] |
| 1 | Energy i.e. sum of the squared discrete FFT component magnitudes of $a_{norm}$ [1] |
| 1 | Correlation between $a_{norm}$ and $a_{vert}$ |

Table 2: Number of computed features.

To estimate the performance of the proposed approaches for fall detection, we perform leave-one-subject-out cross validation (LOOCV) [7], where *only* normal activities from $(N-1)$ subjects are used to train the classifiers and the $N^{th}$ subject's normal activities and fall events are used for testing. This process is repeated $N$ times and the average performance metric is reported. This evaluation is person independent and demonstrates the generalization capabilities as the subject who is being tested is not included in training the classifiers. For the DLR dataset, one person did not have falls data and for the MobiFall dataset, two subjects only performed falls activity; hence these subjects are removed from the analysis. The different values of $w$ tested for $HMM1_{out}$ and $HMM2_{out}$ are $[1.5, 1.7239, 3, \infty]$ and $\xi$ for $XHMM1$, $XHMM2$ are $[1.5, 5, 10, 100]$. The value of $w_{CV}$ for rejecting outliers from the normal activities is set to 1.5. Table 3 and Table 4 shows the performance metrics used in the paper.

| | | **Predicted Labels** | |
|---|---|---|---|
| | | Normal | Falls |
| **Actual Labels** | Normal | True Positive (TP) | False Negative (FN) |
| | Falls | False Positive (FP) | True Negative (TN) |

Table 3: Confusion Matrix

| **Metric** | **Formula** |
|---|---|
| Geometric Mean ($gmean$) [11] | $\sqrt{\frac{TP}{(TP+FN)} * \frac{TN}{(TN+FP)}}$ |
| Fall Detection Rate ($FDR$) | $\frac{TN}{TN+FP}$ |
| False Alarm Rate ($FAR$) | $\frac{FN}{(TP+FN)}$ |

Table 4: Performance Metric

| **Method** | **DLR** | | | **MobiFall** | | |
|---|---|---|---|---|---|---|
| | $gmean$ | $FDR$ | $FAR$ | $gmean$ | $FDR$ | $FAR$ |
| $HMM1_{full}$ | 0 | 0 | 0.0001 | 0 | 0 | 0 |
| $HMM2_{full}$ | 0 | 0 | 0.0001 | 0 | 0 | 0.0001 |
| $HMM1_{out}$ | 0.068 | 0.029 | 0.008 | 0.030 | 0.003 | 0.022 |
| $HMM2_{out}$ | 0.831 | 0.859 | 0.175 | **0.793** | 0.755 | 0.159 |
| $XHMM1$ | **0.883** | 0.882 | 0.102 | 0.413 | 0.222 | 0.224 |
| $XHMM2$ | 0.581 | 0.974 | 0.640 | 0.752 | 0.938 | 0.390 |

Table 5: Performance of Fall Detection methods.

### 5.3 Results

For comparison purpose, we implemented two threshold based HMMs similar to $HMM1_{out}$ and $HMM2_{out}$ with the difference that they are trained on full 'normal' data and the threshold is set as maximum of negative of log-likelihood. We call them as $HMM1_{full}$ and $HMM2_{full}$. Table 5 shows the performance of the $XHMM$ methods along with threshold based HMMs on both the datasets. When the fall data is not present during the training phase, for the DLR dataset, $XHMM1$ has the highest $gmean$ in comparison to other X-factor and threshold based methods. $XHMM2$ has the highest $FDR$ but at the cost of high $FAR$. The reason for poor performance of $HMM1_{out}$ is that most of the falls are misclassified as jumping/running. For MobiFall dataset, $HMM2_{out}$ and $XHMM2$ show higher value of $gmean$ in comparison to other X-factor and threshold based methods, with $XHMM2$ having the highest $FDR$, whereas $XHMM1$ and $HMM1_{out}$ classify most falls as sitting and step in car, thus their performance is greatly reduced. We also observe that $HMM1_{full}$ and $HMM2_{full}$ that are trained on full 'normal' data performed worst and are unable to detect falls due to setting of large negative of log-likelohood threshold due to the presence of outliers in the training data for normal activities.

We also implemented two supervised versions of XHMMs ($HMM1_{Sup}$ and $HMM2_{Sup}$): a) when only 1 fall is used (chosen randomly 10 times and average metric reported), and b) where all the falls data are used, during the training phase. This experiment demonstrates a practical scenario when we have very little falls data and compares it with an optimistic view on collection of data for falls. Table 6 shows that the supervised versions with very small falls data did not show consistent performance for both the datasets, however when all the falls data present is used for training, performance is improved both in terms of higher $gmean$ and $FDR$ and lower $FAR$, except for $HMM1_{sup}$ where most of the falls are misclassified as sitting or step in/out car. Our results show that when there is no fall data available during training time, the supervised methods cannot be used and the performance of these methods is not consistent if very few training data is available.

| **#Falls data** | **Method** | **DLR** | | | **MobiFall** | | |
|---|---|---|---|---|---|---|---|
| | | $gmean$ | $FDR$ | $FAR$ | $gmean$ | $FDR$ | $FAR$ |
| 1 | $HMM1_{Sup}$ | 0.247 | 0.172 | 0.013 | 0.173 | 0.067 | 0.003 |
| | $HMM2_{Sup}$ | 0.442 | 0.480 | 0.326 | 0.552 | 0.406 | 0.038 |
| All | $HMM1_{Sup}$ | 0.660 | 0.525 | 0.022 | 0.249 | 0.066 | 0.005 |
| | $HMM2_{Sup}$ | 0.729 | 0.709 | 0.174 | 0.875 | 0.837 | 0.083 |

Table 6: Supervised Fall Detection.

## 6 Conclusions

Falling is the most common cause of both fatal and nonfatal injuries among older adults [3]. Recent advancements in ambient assistive living have led to the development of several commercial devices (e.g. Philips Lifeline [16]), MobileHelp Fall Button™ [14] etc). However, these products may fail to identify diverse types of falls, can produce lot of false alarms and require manual intervention. The reason is that the performance of fall detection algorithms is hampered by the lack of training data for falls because they occur rarely and infrequently. With little or no training data for falls, supervised classification algorithms may underperform as they may either underfit or not-model falls correctly. In this paper, we presented two 'X-factor' HMM based fall detection approaches that learn only from the normal activities captured from a body-worn sensor. To tackle the issue of no training data for falls, we introduced a new cross-validation method based on the IQR of log-likelihoods that rejects spurious data from normal activities to help in optimizing the model parameters. The XHMM methods show high detection rates for fall. We also showed that the traditional method of thresholding with HMMs trained on full normal data to identify falls is ill-posed for this problem.

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