VAMPIR- An Automatic Fall Detection System Using a Vertical PIR Sensor Array

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***Abstract*—Falling is a common health problem for elderly. It is reported that about 12 million adults 65 and older fall each year in the United States. To address this problem, at the Center for Eldercare and Rehabilitation Technologies in the University of Missouri we are investigating multiple fall detection systems. In this paper, we present an automatic fall detection system called VAMPIR based on a vertical array of multiple passive infrared (PIR) sensors. PIR sensors provide an inexpensive way to recognize human activity based on its infrared signature. To differentiate between falls and other human activities such as walking, sitting on a chair, bending over etc., we used a pattern recognition algorithm based on hidden Markov models (HMM). We obtained encouraging classification results on a pilot dataset that contained 42 falls and multiple non-fall human activities performed by trained stunt actors.**

Keywords-fall detection; eldercare; PIR array; HMM;

I. INTRODUCTION

Falls are the leading causes of accidental death in the US population over age 65 [1, 2]. In 2007, about three thirds of all people that died as a result of a fall were above age 65 [2]. The death rate caused by falls among elders is increasing quickly over the past decade [3]. Multiple studies showed that delay of the medical intervention after a fall is negatively correlated to its outcomes. If the nursing personnel is informed as soon as possible after a fall they can provide invaluable assistance that may significantly improve the intervention outcomes [4]. One of the possible solutions for reducing the intervention time is to automatically detect and then promptly report the fall to the related medical personnel.

There are multiple companies and academic research centers in US and other parts of the world that focus on finding solutions for prevention and early detection of falls. At the Center for Eldercare and Rehabilitation Technologies (CERT) from the University of Missouri, Columbia, we are also investigating multiple fall detection systems. Early on, during the design of our research strategy, we decided to explore only non-wearable sensors for deployment in elderly apartments. Indeed, multiple focus groups conducted with elderly at that time [5-7] pointed us in that direction. We are currently developing fall detection system based on a variety of non-wearable sensors such as dual web cameras [8], Kinect [9], microphone array [10] and Doppler radar [11]. Each of the above sensors has its advantages and limitations. For example, the dual web camera system [8] has a very low false alarm rate during the day and when the subject is closed to the camera. However, the performance is reduced during light transitions or at the edge of the field of view. The first above issue is addressed when a Kinect sensor is used for gait analysis [9] and fall detection. In this case, the light intensity and change are no longer a problem. The second issue may be addressed by employing a microphone array [10] that has a wide area of coverage. However, the microphone array is sensitive to sound interference. In rooms with strong sound sources (such as TV sets) a Doppler radar fall detection system might be more suitable. The Doppler radar [11] is only sensitive to motion and can penetrate apartment walls.

In this paper we are presenting a new fall detection system based on a **v**ertical **a**rray of **m**ultiple **p**assive **i**nfra**r**ed (PIR) sensor denotes as VAMPIR. The VAMPIR sensor uses multiple PIR sensors (two in this work) at each height level to increase data reliability. This system is ideal for tight spaces where privacy is an issue such as bathrooms. PIR sensors provide an inexpensive way to recognize human activity based on its infrared signature. The pattern recognition algorithm used in this work to discriminate between falls and other human activities such as walking, bending over and sitting on a chair is based on hidden Markov models (HMM).

This paper is organized as follows. In section II, we present the VAMPIR system architecture and in section III we describe the datasets used in this paper. In section IV we give the HMM-based algorithms employed for automatic fall detection and in section V we show the experimental results. The conclusions are given in section VI.

II. VAMPIR SYSTEM ARCHITECTURE

The architecture of the VAMPIR sensor [15] is shown in the picture from Fig. 1. The system consists in four sets of two PIR sensors arranged on a vertical support 1 foot apart from each other. In this research we used a Panasonic MP PIR Motion sensor [12] with a 20° vertical field of view (FOV) and 40° horizontal FOV. The infrared light that is reflected from the human body has a wavelength of about 10 micrometers. Our sensors have an infrared filter which allows only infrared light with a 10 micrometer wavelength [12]. This helps to reduce the effect that non-targeted sources

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of infrared radiation (other than humans) have on the sensing elements. When a human walks through the field of view of the PIR sensing element, the infrared energy which is reflected from their body activates, first the left sensing surface and then the right one. When the left sensing surface is activated, it induces a positive differential voltage at the sensor output. When the right half is activated a negative differential voltage is generated. An example of the typical signal that the sensor would generate for a human body motion is shown in Fig. 2.a. The output signals from the 8 PIR sensors are concomitantly processed to estimate the behavior of a person that is moving within the field of view of the VAMPIR sensor array.

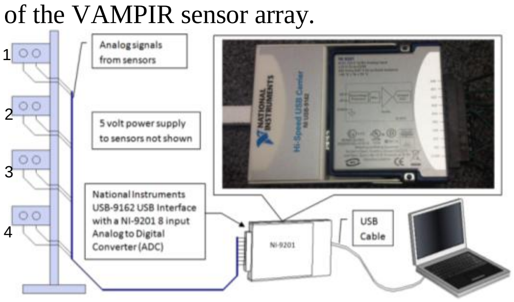
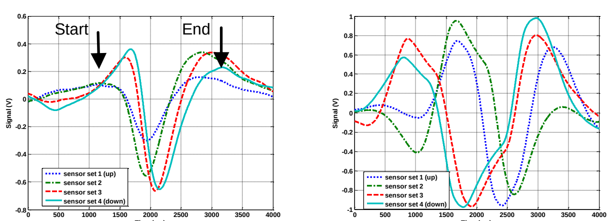


Figure 1. VAMPIR sensor and its experimental setup

In fact, in this work, only 4 signals are used in processing since the (two) signals in the same set (or level, marked 1 to 4 in Fig. 1) are averaged to increase data reliability. From now on, we consider (and refer to) the signal of the sensors from a given level set as a single signal.

The experimental setup used in this paper is shown in Fig. 1. The 8 PIR signals were captured using a National Instruments data acquisition card NI 9201 with 8-channel analog inputs. Sampling frequency was f_s=1000 Hz. The signals were then recorded on a laptop using National Instruments (NI) SignalExpress software and later processed in Matlab (http://www.mathworks.com).



a. Raw fall signal b. Raw non-fall - bending down

Figure 2. Sample fall (a) and non-fall (b) raw signal collected from a VAMPIR sensor.

In Fig. 2 we show a typical output VAMPIR signal for a fall event and a non-fall event. The “start” and the “end” of the fall are marked on the figure, leading to a total length of the fall signal of about $\Delta\tau$=2 s. Although a fall happens in a much smaller time interval (about 0.5 s) we included in the fall signature some of the pre and post impact data. In fact, we can observe a quasi sinusoidal pattern repeated 4 times in Fig. 2.a. We see that, as expected the bottom sensor (no. 4) “sees” the most amount of motion (hence larger amplitude signal) while the upper sensor (no. 1) detects the least amount (hence lower amplitude). In addition, the temporal order of the signal produced by individual sensors shows, as expected, a delay (shift) from the upper to the lower VAMPIR sensor as the upper sensor “sees” action first. In the signals from “bending down” false alarm presented in Fig. 2.b it can be seen that although the patterns of the two sensors 1 and 2 are somewhat similar to the one form a fall, the ones from the lower sensors are shifted to the right as they are starting to see motion in the opposite direction when the person comes back to standing position.

These observations suggest that a fall has a unique pattern of human motion shifting gradually (vertically) from the upper to the lower PIR sensor. Consequently, this implies that the best pattern recognition approach for our problem is a hidden Markov model with N=4 states, that is, state 1 is physically related to sensor 1, state 2 to sensor 2, etc. In section IV we will describe in more details the pattern recognition algorithm used in this work.

III. DATA COLLECTION AND DATASETS

The data used in this paper consists in human activity VAMPIR signatures collected in 42 fall files and 15 non-fall files, respectively. Each fall data file is about 20 s long and contains only one fall. The non-fall data files are about 3 min. long and contain 4-5 non-fall activities per file. In summary, we collected 42 falls and about 50 possible false alarms (non-falls) signatures. The falls were performed by a professional stunt actor. The stunt actor was trained by our nursing collaborators to fall like older adults. We replicated various types of falls such as forward fall, backward fall, left-side fall, right-side fall, etc. The 50 “non-fall” signatures were acquired from various activities performed by 8 human subjects (our entire team). Among the recorded human activities we mention bending over to pick up objects from the floor, kneeling, tying shoes, sitting on a chair, arm/leg swing, walking, etc.

We processed the collected data into two datasets. In one dataset, denoted **DS1**, we included 15 fall and 15 non-fall signatures randomly selected from the 57 available data files. Each signature is 2 s long (similar to the one shown in Fig. 2.a between arrows), that is 2000 samples. We used this dataset to train and tune our HMM fall and non-fall models.

In the second dataset, denoted as **DS2**, we concatenated all our data in one file about 26 min long (about 1.5 million samples). We used this dataset to implement and test a temporal version of an automated fall detection algorithm. We present the results obtained on both datasets in the next section.

IV. AUTOMATIC FALL DETECTION ALGORITHM

A. *Hidden Markov Models for fall sequence recognition*

Assume we have a sequence of observations $\mathbf{o}=\{o_1,\ldots,o_T\}$, $o_t \in R^P$ that are emitted by a system S during transitions between a set of states $\mathbf{q}=\{q_1,\ldots q_T\}$. T is the available observation sequence length. Since states q_t are not observable, we can only describe the behavior of the system using observations o_t. A continuous HMM (CHMM) model, λ, for the behavior of the system, S, can be described as $\lambda=\{A,B,\pi\}$ where [13]:

- N is the number of states in the model;

- $A=\{a_{ij}\}_{i,j=1,N}$ is the state transition probability matrix:
$$a_{ij}=P[q_{t+1}=j|q_t=i], \quad (1)$$
and q_t is the state at time t. An HMM with all $a_{ij}>0$ is called ergodic. This means that any state transition is possible. In a left-right HMM, only transitions a_{ij} where $j\geq i$ are possible.
- $B=\{b_j(o_t)\}_{j=1,N;t=1,T}$ is the observation emission probability density which is the probability of seeing observation o_t when the system is (probably) in state q_j, where:
$$b_j(o_t)=\sum_{k=1}^{M} c_{jk}\mathcal{N}(o_t,\boldsymbol{\mu}_{jk},\boldsymbol{\Sigma}_{jk}),\ j=1, N \quad (2)$$

and $\mathcal{N}$ is a Gaussian distribution with mean $\mu_{jk}\in R^P$ and covariance Σ_{jk}. In this work we set M=1 and Σ_{jk} = diagonal;
- $\boldsymbol{\pi}=\{\pi_j\}$ is the initial state distribution i =1… N, in which
$$\pi_i=P[q_1= i]. \quad (3)$$

In all our current models we assumed N=4 (we have 4 sensors). Also, we set $\boldsymbol{\pi}$=(1, 0, 0, 0) assuming that a fall starts from state 1 (is observed first by PIR set 1). We mention that some falls, from chair or bed for example, might not obey this rule which might be the reason for some of our false negatives. However, the main reason of this assumption is to avoid training $\boldsymbol{\pi}$, due to the small size of our training set.

In order to differentiate falls from non-fall we train two models: one fall model, $\boldsymbol{\lambda}_f$, and one non-fall model, $\boldsymbol{\lambda}_n$. In order to train a HMM model we need a set of K training sequences of length T. Then, the parameters of the model, A, B and $\boldsymbol{\pi}$, are compute using the Baum-Welch equations.

After the two models,$\boldsymbol{\lambda}_f$ and $\boldsymbol{\lambda}_n$, are obtained, we assign a label (fall, not-fall) to an unknown sequence $\mathbf{o}_u$ by choosing the model that best explains the observation. This is performed by computing the likelihoods, $L_f=P(\mathbf{o}_u|\boldsymbol{\lambda}_f)$ and $L_n=P(\mathbf{o}_u|\boldsymbol{\lambda}_n)$, that $\mathbf{o}_u$ comes from a fall or a non-fall event, respectively. The likelihoods are computed using the Viterbi algorithms.

We show neither the Baum-Welch nor the Viterbi algorithm here due to the lack of space. The interested reader is referred to works by Rabiner such as [13]. In this paper we used a simple HMM Matlab implementation, h2m, provided by [14].

The observation sequence o_t was represented using the raw signal (4 features) and the difference between two consecutive sensor signals and the derivative of each signal (slopes), resulting in a total of P=12 features. In addition, we used a sampled version of the raw observation sequence such that the sequence length becomes T=10.

B. *Fall detection algorithm*

Here we used two version of the fall detection algorithm: a single sequence algorithm (SSA) and a sliding window algorithm (SWA). The main SSA steps are:

SSA0: **Input**: a set of K_1 fall sequences $\{\mathbf{o}_f\}$ and a set of K_2 non-fall sequences $\{\mathbf{o}_n\}$. All sequences have the same length T;

SSA1: **Baum-Welch**: Consider one sequence from $\{\mathbf{o}_f\}\cup\{\mathbf{o}_n\}$ unknown, say $\mathbf{o}_u$. Use the remaining $\{\mathbf{o}_f\}$ sequences to train a fall HMM model $\boldsymbol{\lambda}_f$ and the remaining $\{\mathbf{o}_n\}$ sequences to train a non-fall model $\boldsymbol{\lambda}_n$;

SSA2: **Viterbi**: Compute the likelihood difference $\Delta L(\mathbf{o}_u)=L_f-L_n$ where $L_f=P(\mathbf{o}_u|\boldsymbol{\lambda}_f)$ and $L_n=P(\mathbf{o}_u|\boldsymbol{\lambda}_n)$;

SSA3: **Cross validation**: Repeat steps 1-2 above K_2+K_1 times.

Use a set of NT thresholds, $\{\theta_i\}_{i=1,NT}$ for ΔL to compute the receiver operator characteristic (ROC) curve. For a given threshold, if $\Delta L(\mathbf{o}_u)>0$ we label sequence $\mathbf{o}_u$ as "fall", else we label it as "non-fall". By thresholding ΔL with each threshold in the set we obtain NT {true positives, false positives} pairs that are used to plot the ROC. The detection rate for each threshold was computed as (# of falls detected)/K_1 and the false alarm rate as (#false alarms/K_2).

The steps of the SWA are:

SWA0: **Input**: a temporal sequence, **O**, of raw signals of length τ, where length(**O**)>>T; two HMM models $\boldsymbol{\lambda}_f$ and $\boldsymbol{\lambda}_n$ previously computed (in SGA above).

SWA1: Use a **sliding window** $\Delta\tau$=2 s to extract an observation $\mathbf{o}_u$ from **O**, first by downsampling it to length T=10 and then computing the slope and difference features.

SWA2: Compute the **likelihood difference** $\Delta L(\mathbf{o}_u)$ as in SSA1 and 2 above and using the same models.

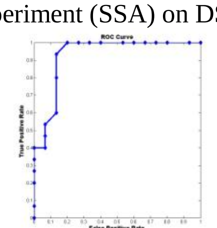
SWA3: Advance window position by 1 s (50% overlap) and repeat *SWA2*.

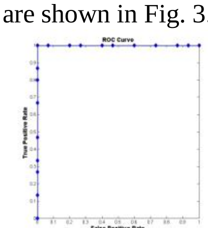
Compute a ROC curve by thresholding the resulting ΔL as in the SSA case above. However, the false alarm rate will be computed per unit of time as (#false alarms/τ min.). Also, after thresholding a post-processing step was performed to merge consecutive hits.

V. RESULTS

A. *HMM training using DS1 dataset*

We decided to choose a number of four states, N=4, for the structure of both HMMs (fall/non-fall). We used a sequence length T=10, which means that we aggregated signal data in time intervals Δt=0.2 s. While the structure of the fall HMM is dictated by the VAMPIR physical structure (i.e. four sensor sets), we chose the same number of states from the non-fall HMM for convenience. We applied the single window algorithm (SSA) with K_f=15 and K_n=15. The ROC curves for the two possible variants, ergodic and left-right, obtained in a leave-one-out cross-validation experiment (SSA) on DS1 are shown in Fig. 3.





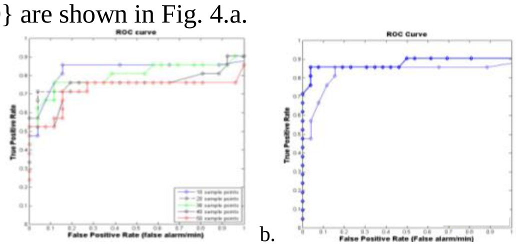
a.ROC for ergodic HMM b. ROC for left-right HMM

Figure 3. HMM results on DS1 data

From Fig. 3 we see that the left-to-right models produce better results (area under ROC, AROC=1 vs. AROC=0.93). This fact has two main explanations. First, the physics of the problem dictates a left-right model for falls. A fall happens when a human body has a fast sequential vertical transition through PIR sensors 1, 2, 3 and 4, respectively. Second, the available training data might not be sufficient to train HMM models with an increased number of variables. In our case, each ergodic model requires training 3 more state transition variables, a_{ij}, than a left-right one.

B. *Automatic fall detection using VAMPIR signatures in DS2 dataset*

The ROC curves obtained using the SWA algorithm on DS2 dataset for various sequence lengths T={10, 20, 30, 40, 50} are shown in Fig. 4.a.



a. b.

Figure 4. (a) The ROC curves for various sequence lengths, T, and (b) improvement obtained by thresholding (bold line) vs. no threshoding (thin line)

From Fig. 4.a we see that the classification performance increases as the sequence length decreases. The “best” performance is obtained at T=10. While the performance itself is not great (detected 85% of the falls with a false alarm every 7 min), we mention that the ROCs presented in Fig. 4.a are useful only for algorithm development purposes.

Next, we improved our previous algorithm by setting a threshold LT (experimentally determined) on both fall and non-fall likelihoods L_f,L_n. Then, L_f,L_n are compared only if both L_f,L_n >LT. If not, no comparison is performed and the window is declared a “non-fall”. The results obtained with this algorithm modification are shown in Fig. 4.b.

From Fig. 4.b we see that by thresholding both model likelihhods (bold line) we significantly reduced the false alarm rate from an alarm every 7 min. (thin line) to one every approx. 30 min (which given the length of our data file, it probably represents 1 false alarm).

VI. CONCLUSIONS

In this paper we present an automatic fall detection system based on a new type of PIR sensor, called VAMPIR. The system measures the relative motion of a human body. Since human falls typically consist in rapid vertical motions that are somewhat unique in their dynamics, it is reasonable to try recognizing a fall based on its VAMPIR signature.

We obtained perfect recognition results for single sequence recognition in a leave-one-out cross-validation experiment on 30 sequences (Fig. 3.b), which means that our approach has the potential to differentiate between falls and non-falls. However, in more realistic experiments (Fig. 4) the false alarm rate is still high while some falls remain undetected.

In future work we plan to investigate the placement of multiple sensors at the same level in a 360° geometry to increase the detection range. In addition, we plan to improve the automatic fall detection algorithm and apply it to realistic datasets collected in our living laboratory (Tiger Place). At the same time, more experiments are needed to address the influence of the distance to sensor on detection performance.

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