Indoor Person Identification and Fall Detection through Non-Intrusive Floor Seismic Sensing

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***Abstract*—This paper presents a novel in-network person identification and fall detection system that uses floor seismic data produced by footsteps and fall downs as an only source for recognition. Compared with other existing methods, our approach is done in real-time, which means the system is able to identify a person almost immediately with only one or two footsteps. An adapted in-network localization method is proposed in which sensors collaborate among them to recognize the person walking, and most importantly, detect if the person falls down at any moment. We also introduce a voting system among sensor nodes to improve accuracy in person identification. Our system is innovative since it can be robust to identify fall downs from other possible events, like jumps, door close, objects fall down, etc. Such a smart system can also be connected to smart commercial devices (like GOOGLE HOME or AMAZON ALEXA) for emergency notifications. Our approach represents an advance in smart technology for elder people who live alone. Evaluation of the system shows it is able to identify people with one or two steps in a 96.06% (higher accuracy than other methods that use more footsteps), and it detects fall downs with an acceptance rate of 95.14% (distinguishing from other possible events). The fall down localization error is smaller than 0.28 meters, which it is acceptable compared to the height of a person.**

***Index Terms*—In-network system, person identification, fall detection, seismic sensing, real-time**

I. INTRODUCTION

Non-invasive approaches for activity monitoring and assisted living represent an innovative smart technology for elder people. Person identification and fall detection are essential components in smart assisted systems that can help to improve people lives. Each year, millions of people, especially those in elderly age, fall in their homes [1]. In fact, more than one out of four older people falls each year [2]. According to the *Center for Disease Control and Prevention*, over 800,000 patients a year are hospitalized because of a fall injury, most often because of a head injury or hip fracture [3]. In addition to these facts, the number of elder people living alone and/or with occasional caregivers is growing around the world [4]. It is clear then, fall detection at home is a problem that must be addressed in a prompt manner. Furthermore, monitoring the person (by identification) is vital to diminish emergencies. Even though some solutions for elderly monitoring are available on the market, most of them are either body-contact equipment [5] or privacy-invasive devices (like cameras or similar) [6].

Pervasive computing plays a key role in person identification and fall detection. Privacy and comfort are two important issues to incorporate in the solution. In this paper, we propose a novel in-network person identification and fall detection system that uses floor seismic data produced by footsteps and fall downs as an only source for recognition. The system is based on the analysis of structural vibration where sensors sense floor vibrations, perform in-situ signal processing, identify a person via footsteps and detect fall downs. Because the main source of data comes from floor vibrations, the sensors are installed on the floor (for example, in the corners of a room), and there are no cameras or other privacy-invasive devices. Also, our approach is able to discriminate other events in the room, and differentiate when it is related to a fall down or a footstep. The system is able to identify a person almost immediately with only one or two footsteps.

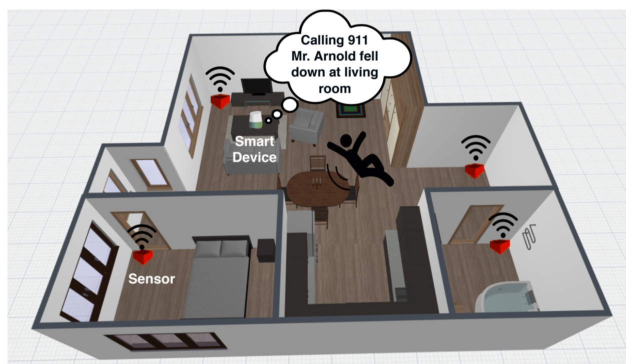


Fig. 1: System Detection and Localization.

As a novel feature, the system is also able to locate the place of the fall down with an acceptable error. Fall location is achieved through collaboration and cooperation between sensor nodes. We introduce an adapted in-situ fall localization method that is in-network performed. Sensors communicate each other when they detect a fall down and cooperate among them to locate the place of occurrence. The innovations of our in-network person identification and fall detection system are summarized as follows:

- A **end-to-end real-time** system that is able to identify people through floor vibration produced by footsteps. The method includes features extraction via in-situ signal processing and recognition via machine learning techniques. The method is done in-network, and it recognizes a person in one or two steps, improving other existing approaches

that use at least five steps [7]. An optimization method is used for improving the feature extraction.
- An adapted **in-network localization method** is proposed in which sensors collaborate among them to spatially localize footsteps, and most importantly, falls down in real-time.
- A **voting system** among sensor is implemented to improve the identification accuracy. Sensors collaborate and talk to each other to decide which person is walking.
- **Integration with commercial smart assistants** (like GOOGLE HOME or AMAZON ALEXA) is provided to interact with the external world when a fall is detected.

The rest of the paper is structured as follows: Section II presents the related work and highlights the advantages of our proposed approach. We describe our system design in Section III. Our experiments and validation, as well as the discussion of results, are presented in Section IV. We conclude the paper in Section V.

II. RELATED WORKS

A great variety of works have focused the attention on person identification via footstep and fall detection. In this section, we discuss previous work on this area, their implications and the benefits of our approach respecting them.

Person identification via footsteps and fall detection is a research area for recognizing, identifying and tracking different individuals based on the step signal characteristics. Many applications are based on smart flooring system where a special kind of floor needs to be installed for identification purposes [8]–[11]. Even though the recognition accuracy is good enough (average of 90%), the need of floor installation can be unsuitable for smart houses. Other approaches use image processing techniques to detect fall downs [12], [13]; however, having cameras may be considered as a privacy-invasive method.

An in-door person identification through footstep induced structural vibrations was presented in [7]. The system senses floor vibration, detects signals induced by footsteps, extracts signal features, and applies a hierarchical classifier to identify each registered user. The work is based on the assumption of each person has a unique walking pattern due to many factors, including individual physical characteristics, the center of gravity position during the walk, the way feet contact the ground, etc. In the decision making part, the system takes features from different peoples traces to generate a classification model using Support Vector Machine (SVM), which maximizes the distance between data points and the separating hyperplane. Our approach is quite similar, however, as it will be shown, our main differences are: (i) we extract different features that exhibit better accuracy; (ii) we can identify people using only two footsteps in contrast with the five needed for this approach; (iii) therefore, our method is faster.

In [14] a footfall detection method was presented using seismic signals collected by a geophone. The methodology is based on an unsupervised learning detection with these steps: (i) clustering to separate noise and footfall events from an unlabeled dataset using Gaussian mixture models (GMM) based clustering technique; (ii) The Class-labeling section labels the clusters as event (Class1) and noise (Class2). GMM assumes that the features of both the clusters follow a multivariate Gaussian distribution; (iii) training and testing the model. Even though they were able to detect steps using seismic signals, their work does not identify people according to the study of the footstep. Alwan et al. [15] also presents a fall detection method based on floor vibration. The works report 100% of accuracy; however, the main analyzed feature is the amplitude of the signal, and there is not an explicit comparison with other human activities that have similar amplitude (example an object drop, jumping on the floor, closing doors, etc.)

Our approach improves the aforementioned works by not only identifying people based on the footstep analysis, but also detecting when a person falls down, in which location the fall down occurs, and which person falls down. Also, our sensors allow communication and cooperation for generating real-time results without the need of post-processing.

III. SYSTEM DESIGN

The in-network system is designed based on the footstep vibration measured by smart seismic sensors attached to the floor. Our seismic sensors are able to measure biometric signatures, like footsteps and/or fall downs, and collaborate among them to locate the fall down place without the need of extra sensor devices like cameras. The system architecture is presented in Fig. 2. Every sensor performs the steps described in the architecture and communicates each other to detect fall down place in the "localization" step. In this section, we present the details of each step and the logical structure of our system.

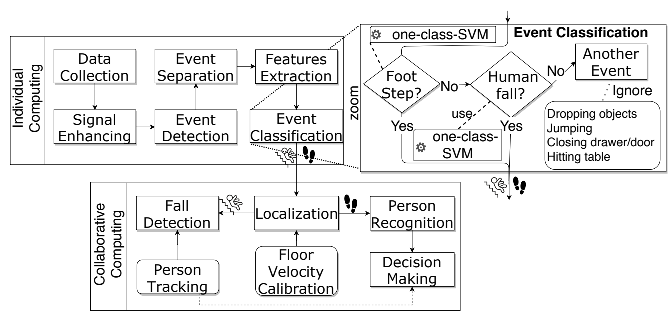


Fig. 2: System Architecture.

A. Data Collection

The vibration measured from the structure is gathered by a smart seismic sensor. The detail description of the sensors is specified in Section IV-A. The three-channel seismometer used in our sensors has a sampling rate of 1000 Hz which is wide enough to detect both low and high-frequency components. The data are recorded in an internal database for further analysis; however, the footstep recognition, fall detection, and fall location are done in real time. Then, the sensors in the seismic network need to be synchronized. When the system starts, each unit synchronizes its time via GPS located inside the unit.

B. Signal Enhancing

In any in-door place exists background noise due to constant building shaking. This background noise tends to obscure the different events we need to detect, especially the footsteps. To enhance the signal, we attempt to remove the background noise by applying a wavelet denoising technique on the data to suppress non-stationary noises. The denoised signal s_d using wavelet thresholding can be expressed as [16]:

$$s_d = \sum_{j,k \in K} \tau \left(\int s(x) \psi_{j,k}(x) dx \right) \psi_{j,k}, \tag{1}$$

where, $(\psi_{j,k})_{j,k \in K}$ denotes the orthogonal basis of wavelets, $\tau(\cdot)$ is the thresholding operator.

C. Event Detection and Separation

Once the signal has been enhanced, an event detection technique is applied to separate the events. Footsteps and fall downs are considered events. We apply a signal isolation technique to extract the pulses of footsteps and fall down vibration [17]. This process is important for future determination whether an event represents a footstep, a fall down, or something else. Our isolation is different from those used in other works. For example, in [18], the event detection is based only on the time of arrival (ToA); the time when the event finalizes is not considered. We implement an on-line changing point detection algorithm to find abrupt variations in data to pick the event. It is based on a probabilistic method - first-order second-moment method - to determine the stochastic moments of a signal. The first-order second-moment method is defined as:

$$m_2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2, \tag{2}$$

where μ is the mean of the distribution, and N is the windows size of the data to be processed. We use a 50 milliseconds window to find changing points with low latency. An event starts when the moment m_2 is larger than a threshold. We set up the threshold at three times of the standard deviations of the background noise, which is updated constantly with data that does not come from an event. An event culminates when m_2 is below 1.5 times of the standard deviation.

D. Feature Extraction

The feature extraction procedure is essential for footstep and fall down characterization. As reported in [19], it is possible to distinguish a human footstep vibration signal from background noises by selecting the correct features. Different approaches have been adopted in literature for extracting a set of features that help to obtain signatures of footsteps. For example, features extracted from mean vectors and covariance matrices of spectral coefficients were used in [20]; other works use short-term energy and footstep intervals [21], as well as gait-based information as main features for footsteps representation [22]. Because the vibration and sound pressure responses of human footsteps in buildings can be broadband and frequency-dependent [23], and different vibration signatures from different walking styles can be studied [24]. We compute features in both, time and frequency domain. Before obtaining the features, we normalize the signal events to eliminate the distance effect between the sensor location and the event location. The normalization is done by dividing the event amplitude by the energy of its signal. We adapt the features used on [7]. Also, we analyze the duration of the events and number of peaks in the time of data of detection. These additional features help to improve the score of the people and detect falls in the studied area. An optimal selection of the features is also adopted to improve the person identification, which is explained in Section III-G2. Table I shows the features extracted from the events and the labels used as abbreviations.

TABLE I: Event features.

Domain	Label	Feature Name	Label	Feature Name
Time	F1	Event duration	F5	Maximum peak
	F2	Standard deviation	F6	Location of maximum peak
	F3	Entropy	F7	Five values before maximum peak
	F4	First five peak values	F8	Five values after maximum peak
Frequency	F9	Spectra	F12	Location of first five peaks
	F10	Centroid	F13	Number of peaks
	F11	First five peak values		

E. Classification

Precise classification is the main point of our system because it works based on two types of events; footsteps and human falls. We use footsteps to identify a person and falls to calculate the location and generate an emergency. However, there are many events in daily life that generate vibrations that are sensed by our geophones. Many of these events have similar characteristics which must be selected and classified in order to get footsteps and human falls. For example, a jump can generate an event that has an amplitude in time domain similar to that of a fall, but these can differentiate using the duration time and the number of peaks in time domain (both are greater in fall events). Similarly, events such as closing a door, or falling an object have characteristics like human falls. Other events such as hitting a table or closing a drawer have similarities with the steps of a person.

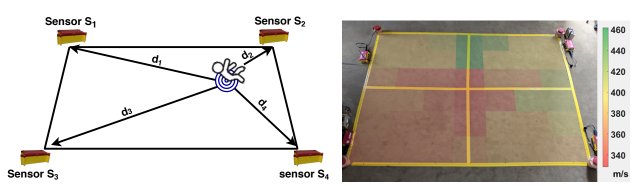
We based our classification process in a supervised machine learning algorithm, a Support Vector Machine (SVM), which transforms the data using a kernel to find the optimal boundary between the different classes. The event classification workflow is presented zoomed in Fig. 2. The inputs are the features extracted from each event detected. We are using two independent classifiers that are placed in two layers. The first is to identify if the event is a footstep. Otherwise, the features are sent to the second layer to identify if it is a human fall. The event is discarded if it does not belong to either of these two classes. The footstep classifier is located at the beginning of the process for two reasons. First, it is the most common event present in our system where more than 90% of the events are footsteps. Second, because we have much more training data for this SVM and the accuracy for identifying footsteps is higher compared with other events.

Both classifiers were implemented using one-class-SVM to be able to discard events of which there is no data for their training. For example, an earthquake is an uncommon event that can be detected by our system and because it is not a footstep, or a human fall is discarded by the classifier.

F. Location

The two type of events, fall and footstep, are located by our system in real-time. The fall location is used to send an alarm with the position where the event is presented, and the footstep location is implemented for person identification and tracking. It allows to identify the person who fell based on the location of previous steps. Also, it reduces false positives that may appear far from the person's location. Fig. 3(a) shows our seismometer-based location system.

Location techniques require the prior knowledge of the propagation speed and the seismometer locations. They also need several units to detect the event location. We incorporate four units to reduce the location error margin. In addition, all the seismometers should be synchronized in time. Since the GPS accuracy is lower inside a building and the seismometers are placed too close for the satellite positioning system, we need first manually setup the relative sensor locations. Then, in the defined coordinates, a jump synchronization process is applied to initialize the wave propagation velocity model of the floor. The process involves jumping twice next to each unit. Then, all sensors broadcast the arrival time of the event, and the sensor with the minimum arrival time calculates the speed having the assumption that the jump was made in its location. After eight events the sensors generate the velocity model of the floor. The calibration result of our floor is shown in Fig. 3(b).



(a) (b)

Fig. 3: (a) Seismometer-based location system. Seismic sensors cooperatively calculate the event localization, (b) Initial velocity map for calibration purposes of our system. A jump synchronization method was performed to initialize the wave propagation velocity model of the floor.

1) Time Difference of Arrivals (TDOA): We estimate the event location adapting the time difference of arrivals (TDOA) between all time-synchronized stationary sensors $\mathbf{s_m} = [x_m, y_m]^T$, $m = 1, ..., M$ to locate where the event $\mathbf{e} = (x, y)^T \in \mathbb{R}^2$ is generated (source). Every single node determines the event arrival time. The TOA is composed for the time when the event starts $\mathbf{t_0}$ and the transmission time between the source and sensor $\mathbf{m}$:

$$\tau_m = t_0 + \frac{d_m}{v}, \tag{3}$$

where

$$\begin{aligned} d_m &= \parallel \mathbf{e} - \mathbf{s_m} \parallel \\ &= \sqrt{(x - x_m)^2 + (y - y_m)^2}, \quad m = 1, ..., M \end{aligned} \tag{4}$$

denotes the Euclidean distance between the source and sensor m, and v is a constant speed. The range measurement function is obtained by multiplication the TOA measurements in the time domain with the velocity v:

$$r_m = d_0 + d_m \tag{5}$$

where $d_0 = vt_0$ is the time of emission multiplied with v.

TDOA calculates the difference between two TOA measurements and eliminating the unknown time of emission:

$$r_{i,j} = d_i - d_j, \quad i, j \in \{1, ..., M\} \land i \neq j \tag{6}$$

TDOA measurement between each pair of nodes defines a hyperbola of likely event locations. The equation parameters are the known sensors location and the event location.

2) Location Estimation: We propose to use an optimization method to estimate a two-dimensional position vector. We eliminate the assumption of constant speed [25] due to the propagation velocity value is not constant. V is the propagation velocity matrix obtained from the calibration process. We use Maximum Likelihood (ML) estimator to calculate the position vector $\mathbf{e}'$ which maximizes the likelihood function or rather minimizes:

$$t' = \underset{t}{\operatorname{argmin}} \sum_{i=1}^{M} \parallel \widetilde{\tau}_i - \tau_i \parallel \tag{7}$$

Subject to:

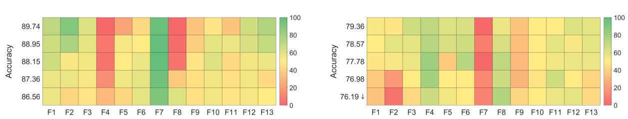
$$\begin{aligned} &\min_{sx} \leq x \leq \max_{sx} \quad sx \in \mathbf{s_m}[x_m] \\ &\min_{sy} \leq y \leq \max_{sy} \quad sy \in \mathbf{s_m}[y_m] \\ &M > 2 \end{aligned} \tag{8}$$

We use Nelder and Mead as numerical iterative search in a multidimensional space. The previous event location (step or fall) is set as the initial points of the algorithm, and if there is no previous event registered the points are generated randomly next to the unit with the minimum event arrival time. Based on our experiments we used a threshold of 1.5 milliseconds as a stopping criterion.

G. Person Recognition

We implement a multi-class-SVM [7] as a supervised classification algorithm because it provides two main advantages. First, it has linear kernels to classify the classes using the features from the floor vibrations induced by the footsteps. Second, although SVM is computationally expensive for training, its search is fast enough to be implemented on a single computer board. The training is done previously in a machine with good computational resource. The multi-class-SVM fits perfectly in the requirements for our person recognition method.

1) Feature Selection: We trained the multi-class-SVM using the features proposed in [7]. We noticed that these features do not contribute to the classification model to recognize people with good accuracy. For that reason, we implement a test and a numerical analysis to determine which features contribute or not to the model. This allows us to remove and add features. We cannot apply linear regression because our kernel is not linear. During the test, we use data from four people to avoid over-fitting. In the testing step, we test with new data from these four subjects, and we add two additional people. The test purpose is to optimize the features used by the multi-class-SVM to reduce the dimension number and improve accuracy. We execute the test combining all the characteristics obtained from the footstep events, taking from F5 to F13 features. Two new features are introduced during the training (event time duration and number of peaks in the frequency domain). Accuracy heat maps are shown in Fig. 4, colors of which represent the contribution proportion of the features to obtain the related accuracy. Green color means major contribution, and red color refers to features that do not contribute to a specific accuracy value. Fig. 4(a) shows the top 5 accuracies obtained in the test. It is clear that features F4 and F8 do not contribute in a large proportion to obtain these values. While the two features included, F1 and F13, add information to the SVM model in more than 80% of the cases. In contrast, Fig. 4(b) shows the lower accuracies obtained. In the same way, features F4 and F8 are contributing in more than 70% of cases to obtain these low accuracies. The remark of this optimization test is to remove characteristics F4 and F8 and keep the new two features (F1 and F15). We improve the accuracy in more than 5% respecting to the use of features from F2 to F12 only.



(a) (b)

Fig. 4: Feature selection test heat map. (a) Five best accuracy values of the test , (b) Five worst accuracy values; the last value 76.19↓ stands for all accuracies below 76.19%.

2) Decision Making: We incorporate four units to locate the events as we explain in the previous subsection. In the same way, these units work together to recognize people through the floor vibrations induced by footsteps. The energy signal is different in each unit because the signal degrades during transmission. Normally, the unit closest to the event source is the unit with the highest energy event. However, internal floor structures cause that in some areas, the signal degrades more than in others, even if the units are placed at the same distance. The signal degradation causes that some events do not have the correct features for recognizing a person. It produces false positives reducing the system accuracy. For this reason, we make a weighted collaborative decision making or weighted voting system (WVS). The weights are based on the energy event. After the individual person recognition, each unit broadcasts the event energy and the person id number in the tuple $\Phi_i = [\mathcal{E}_i, \mathcal{P}_i]$ where $i = 1, ..., M$.

The unit with the highest event energy calculates and identifies the person. We use a weighted voting decision making, in which the weight is calculated as:

$$\omega_i = \frac{\mathcal{E}_i}{\sum_{j=1}^{M} \mathcal{E}_j}. \tag{9}$$

The decision is then calculated based on the weights obtained by each identified person represented as a subset $H \subset \mathcal{P}$ without duplication.

$$\sum_{j=1}^{|H|} \sum_{i=1}^{M} \mathcal{S}_j = \omega_i; \quad \forall H_j = \mathcal{P}_i \tag{10}$$

where $|H|$ is the size of the subset H (e.g. if there are 5 people identified by different unit in the process; then $N = 5$). The selected person is H_x where x is the index of the maximum value in $\mathcal{S}$. After the recognition, the unit communicates the person name to the smart assistant which is in charge of issuing a greeting message, e.g. "Hello Adam".

H. System Alert

When the recognized event has been classified as a fall down (see Section III-E), a system alert is activated to verify if the event was a real fall down or it is a false positive. The method used for doing this fall down recognition is described as follows: (i) a fall down is detected by the classifier; (ii) the area in a radius of 1.5 meters around the location of the last recognized step is analyzing; (iii) if the localization of the event falls into this area, the system ensure that the recognized event is, in fact, a fall down. This mechanism improves the accuracy of the system by eliminating other events that can generate false positive recognition such as: dropping an object far away of the person, closing a door or drawer, hitting a table. However, the system may still recognize some others events like jumping as fall down events.

In addition, when the fall down is recognized, an alert is sent to a smart home device. We use GOOGLE assistant library for connecting our nodes with this smart device (GOOGLE HOME). Using this API, the unit sends an internal message to the smart device that provides an instruction to be completed. For now, the smart device alerts via sound the event occurrence. However, more features can be easily added, such as 911 calls or family members calls.

IV. EXPERIMENTS AND VALIDATION

In this section, we describe the details of the experiments conducted with our in-network footstep and fall detection system. Instead of using simulated data, we use real devices and a footstep-seismic testbed to validate our methods. First, we present the hardware deployed for testing our system, and then, the results of each step (person identification, fall detection, fall location) are presented. In the scenarios where we use classifiers, the data used for the training and the tests were split into a radius of 80/20. A discussion of the results is also provided at the end of the section.

A. Hardware and Software Setup

We use real sensor units for our experiments. Each unit has a three-channel seismometer, a single computer board (Raspberry Pi 3), a lithium battery as shown in Fig. 5(a). The three-channel seismometer detects the velocity of ground movements. Each channel records its own data with respect to its axis X, Y, and Z, which correspond to directions North, East, and Depth. The single-board computer (Raspberry Pi 3B) collects, stores, processes and communicates data. The battery used is a waterproof battery 11V. We initialize the location of each sensor during the system installation. The nodes are integrated into a mesh network for communication purposes. The smart device that is used in the experiments is connected in the same mesh network. Originally, the hardware we used was conceived for outdoor experiments [26], [27]; however, its characteristic makes it suitable for our indoor purposes. Currently, we are working toward the design of smaller hardware with the same features for indoor purposes.

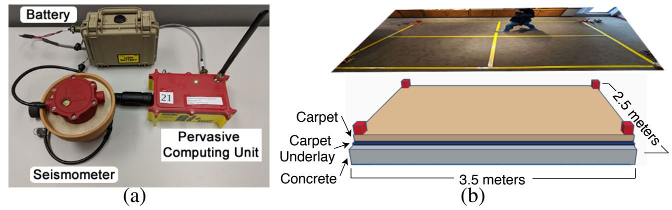
The software inside each unit is developed using PYTHON. We save the data inside each unit using INFLUXDB [28] database that is suitable for time series data monitoring and analytics. The data also is synchronized to a central server for visualization purposes. Results of time of arrival and event location (footsteps and fall downs) are also saved using INFLUXDB. The visualization is performed using GRAFANA [29]. On the other hand, for SVM purposes, we use the library SCIKIT-LEARN [30]. Two types of SVM are used: (i) one-class SVM to distinguish between footsteps/fall downs and other events, and (ii) a multi-class SVM to differentiate between different people. The SVM uses a kernel poly of degree 2, with a penalty parameter C of the error term established in 100.

B. Sensor deployment and footstep-seismic testbed

Our footstep-seismic testbed consists of four sensors deployed in an area of 380 square feet approximately. The sensors were deployed in an area with a square shape. A wireless connection was set up to allow the units to form a mesh network to "talk" among them. We also design a Graphic User Interface (GUI) in Grafana to visualize the footstep and fall down results. Fig. 5(b) shows an overview of our footstep-seismic testbed and the four units deployed on the corners.

C. Event classification

We measure the accuracy of our SVM classifier to distinguish between a footstep, a fall down, and other events. In Table II are presented the results in a confusion matrix. The method we use is able to differentiate between the different types of events with an accuracy of 92.35% and a precision of 89.30%. Note that the percentage of recognition of footsteps is very high. This is due to the training set contains much more footsteps events than other types of events.



(a) (b)

Fig. 5: (a) Sensor unit hardware. Visible at the picture: a battery, a seismometer and a boxed pervasive computing unit. (b) Testbed for the footstep/fall down recognition system.

TABLE II: Confusion matrix of event classification.

Ground Truth			Evaluation		
	Footstep	Other	Recall	Precision	Accurracy
Footstep	417	23	**0.9478**	**0.8930**	**0.9235**
Fall down	8	42			
Jumping	8	90			
Dropping object	12	98			
Closing drawer	6	88			
Closing door	4	64			
Hitting table	12	82			

If an event is classified as a footstep, the next set of results to analyze is the person identification accuracy (Section IV-D). Similarly, is the event is identified as a fall down, we analyze both fall down detection accuracy (Section IV-F) and fall location accuracy (Section IV-G).

D. Person Identification Accuracy

To measure the accuracy of our person identification method, we test our system with six (6) different people. These subjects are named with letters from A to F. The first confusion matrix (Table III) shows the recall, precision and accuracy measurements of the person identification method using only one footstep. As it is shown, the accuracy is 89.49%, which is somehow acceptable. However, the precision is low, only 74.16%. This precision may introduce a high number of false positives in the recognition step. The recognition step in this test includes the use of the voting decision-making technique explained in Section III-G2.

TABLE III: Confusion matrix of person identification using **one** footstep. Subjects are named with letters from A to F.

Ground Truth							Evaluation		
	A	B	C	D	E	F	Recall	Precision	Accurracy
A	75	4	0	4	0	17	0.7500	0.8152	0.9132
B	17	65	0	5	0	13	0.6500	0.5752	0.8419
C	0	0	81	0	19	0	0.8100	0.7642	0.9095
D	0	11	8	76	3	2	0.7600	0.8444	0.9189
E	0	0	17	0	83	0	0.8300	0.7905	0.9189
F	0	33	0	5	0	62	0.6200	0.6596	0.8633
Average							**0.7367**	**0.7416**	**0.8943**

To improve the accuracy of the person identification, we allow the system to analyzed two footsteps instead of just one. The process is the same explained in the workflow, but in the voting decision-making step, two steps are counted for voting, which means that two tuples are sending for decision $(\Phi_i(t)$

TABLE IV: Confusion matrix of person identification using **two** footsteps. Subjects are named with letters from A to F.

	Ground Truth						Evaluation		
	A	B	C	D	E	F	Recall	Precision	Accurracy
A	93	0	0	0	0	7	0.9300	0.9490	0.9780
B	5	84	0	3	0	8	0.8400	0.7706	0.9287
C	0	0	89	0	11	0	0.8900	0.9674	0.9745
D	0	6	0	94	0	0	0.9400	0.9307	0.9745
E	0	0	3	0	97	0	0.9700	0.8981	0.9745
F	0	19	0	4	0	77	0.7700	0.8370	0.9336
Average							**0.8900**	**0.8921**	**0.9606**

and $\Phi_i(t-1)$). Table IV shows the result using two footsteps. Note that the accuracy was improved in more than 5% and the precision was increased to 89.21%, which significantly reduce the number of false alarms.

A detailed analysis of the results and a comparison with the physical characteristics of the subjects in the study show that the false positives we still have are due to similarities in the physical features of the subjects. For instance, subject B and F are both men with almost the same height and an approximate same weight. Those subjects are easy to misidentify. However, footstep features are different enough to get an acceptable accuracy and precision measurements.

E. Decision Making Based on Weighted Voting System

We compare our weight based voting decision making with a simple majority based voting system. Using our weighted method, accuracy, precision and most importantly recall improve. Table V shows the results of both methods. Note that with a single voting decision making there are some no possible decisions since we are using four units in the experiment. No possible decisions occur when two units identify the person as subject A, and the other two as subject B. With our weighted voting, we ensure a decision even in these scenarios.

TABLE V: Comparison of person identification using the weighted voting system (WVS) and single voting (SV).

	Recall	**Precision**	**Accurracy**	**No Possible Decision**
1 Footstep SV	0.5834	0.6856	0.8334	0.1383
1 Footstep WVS	0.7348	0.7037	0.8974	0.0000
2 Footsteps SV	0.7917	0.8812	0.9363	0.0766
2 Footsteps WVS	0.8882	0.8845	0.9625	0.0000

F. Fall down Detection Accuracy

The second one-class SVM is executed once an event has been detected as other class different from footstep. If the SVM is used without taking into account the person who is walking (using the whole area of study) the number of events misidentified is very high. However, when we introduce the method explained in Section III-H, the number of misidentified events is reduced drastically. The method consists of analyzing a radius of 1.5 meters from the last recognized footstep. Results are shown in Table VI.

The Fig. 6 shows the improvements in terms of recall, precision, and accuracy once the 1.5 m radius area is applied.

TABLE VI: Comparison of event classification number as fall down and/or other events. Results are shown using the whole area vs. a 1.5 m radius from the last recognized footstep.

	Using the whole area		**Using a 1.5 m radius from the last footstep**	
	Fall	Other	Fall	Other
Fall	43	7	43	7
Jumping	41	57	8	90
Dropping object	46	64	8	102
Closing drawer	25	69	2	92
Closing door	9	59	0	68
Hitting table	11	83	0	94

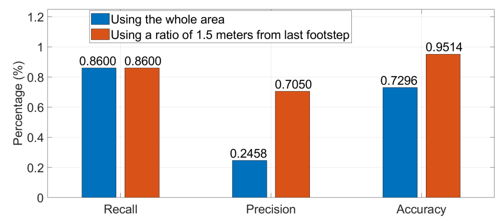


Fig. 6: Comparison of recall, precision, and accuracy between using the whole area and a 1.5 m radius from the last step.

G. Fall Location Accuracy

To test our fall down location method, we use 31 different fall down events inside our testbed to measure the error between the real and estimated location from our method. The average error between them is estimated at 0.27 meters. An example of six different events is shown in Fig. 7. Note that our estimated location is near to the real event location and inside a calculated error area. The error area is calculated according to our sampling rate (1000Hz) and our initial velocity model. The error area is approximately 0.47 meters. All estimated events are inside this area. This estimated area is acceptable since when a person falls down, his body occupies an area of at least 1.5 meters. This means that it will be always a part of the body inside the error area.

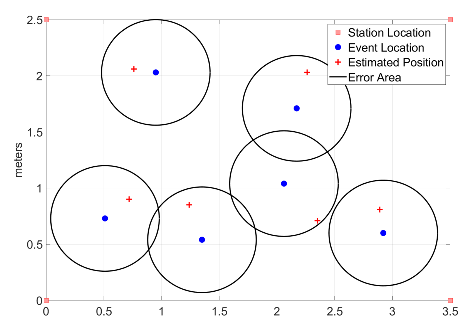


Fig. 7: Six different events location and the comparison between real event location and estimated location obtained with our method. Black circles represent the error area.

V. Conclusion

In this paper, we introduced a novel in-network person identification and fall detection system that can be used in smart homes for many purposes (e.g. elder assisted living). The system is based on the vibration that footsteps and fall down generate on the floor. After data collection with real sensor-smart devices and signal enhanced, we performed a feature extraction technique that characterizes footsteps and fall downs. The feature selection was improved with an optimization technique that indicates which features contribute more to the accuracy of our method. We use different types of SVM to classify the features and recognize the person who is walking. All these steps are performed in-network and in real time. An adapted in-network location method is proposed to localize the footsteps and most importantly the fall downs. The method includes communication and independent cooperation between sensor nodes. A voting decision making is then performed to accurately identify people. Finally, an integration with commercial smart home devices is provided to generate system alerts when it is needed. Experimental results in a real footstep-vibration testbed are presented. We show our method outperformed other existing methods that need to use more footsteps sensing to recognize people. To the best of our knowledge, we are presenting for the first time an in-network fall down detection and location with structural vibration data.

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