

# Human Tracking and Identification using a Sensitive Floor and Wearable Accelerometers

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**Abstract**—We describe a method for user tracking and localization based on textile capacitive sensor arrays placed under the floor. The sensor array is a commercial product (SensFloor<sup>®</sup>) that can be installed under any standard floor type (from carpet to stone) and is able to detect objects (including the user's foot) being placed on it. The challenges addressed in this paper are (1) how to map sequences of such signals onto user trajectories and (2) how to correlate the steps detected by the SensFloor system with the step detection based on a wearable accelerometer as means of user identification. Footstep detection is performed on-line on the devices, which are seamlessly integrated with the floor's wireless sensor network. Initial experiments performed over a week in a real life office environment show the ability to track multiple humans and to identify up to three users walking in a narrow corridor at the same time.

## I. INTRODUCTION

An important aspect of pervasive systems is the ability to locate a person and track his/her movement over time. This allows, not only to provide the user with context aware assistance, but also to record user activity, such as walking patterns and trajectories. Furthermore, tracking grants the system the ability to act preemptively. Take the simple case of a person going from one room to another. By estimating the direction of the movement, the lights in the room the user is heading towards can be switched on before he/she enters. In addition to tracking, user identification improves the overall awareness of the application, where custom interfaces, that take into account personal preferences, adapt to different users in different locations within the smart environment.

Indoor localization and tracking systems can rely on different sensor setups. On one hand, large-area passive sensor systems, like pressure sensitive floors, are unobtrusive and can be seamlessly integrated in the environment. For instance, [3][4] use pressure sensitive floors to track and identify humans, based on their footstep profile. However, tracking multiple persons becomes increasingly difficult if they stand close to each other ([16] complement a pressure sensitive floor system with cameras in order to increase performance in such cases, albeit raising privacy issues). On the other hand, active systems, like IR badges [18] or mobile phones [17], are able to distinguish between users in the area, but have worse performance when it comes to positioning accuracy.

In this paper, we show how we use SensFloor [1], a textile-based large-area sensor system, comprised of a grid of capac-

itive sensor plates under the floor, for human localization and tracking. The sensor system does not allow for a natural user identification (as in [3]), however, the capacitive measurement approach provides more flexibility when it comes to the floor covering. We combine the floor system with small user-bound devices, equipped with an accelerometer, which are integrated with the floor's sensor network, in order to identify users.

In ([1][2]) we described SensFloor and its applications in the AAL domain. Here, we improve our previous work by analyzing the way a foot can be placed on the floor, considering the sensor plates' arrangement, and by describing the process of extrapolating the position of a user from his/her footsteps. Furthermore, we track users by means of Kalman filtering and present a probability based data fusion algorithm, for user identification, using both sources of footstep signals.

The remainder of the paper is organized as follows. Section II gives a description of SensFloor, its main components and possible applications. Section III describes the human localization algorithm, from cluster identification to multi-user tracking. In Section IV, we describe the footstep detection on the individual user-bound devices and its integration with SensFloor, as well as our solution regarding user identification. Section V presents our experimental setup and some results coming from the implementation. Finally, Section VI concludes the paper and gives an outlook for future development.

## II. SENSFLOOR

SensFloor is a textile-based large-area sensor system comprised of an underlay with embedded microelectronic modules, which can be seamlessly installed underneath the floor [2][1]. Using capacitance proximity sensing, as opposed to pressure sensitive floors [3][5], allows for its installation beneath both soft (i.e. carpet, PVC) and hard (i.e. tiles, wood) surfaces.

A typical SensFloor unit, (0.5m x 0.5m), has a sensor module with eight surrounding triangular sensor pads, resulting in 4 units and a spatial resolution of 32 sensor plates per square meter (Figure 1 shows a room being equipped with SensFloor).

Each of the embedded system-on-chip devices performs the capacitance measurement, as well as consequent signal filtering. Furthermore, these contain a radio transceiver, working on the 868 MHz frequency range, which transmits events to one or more central receiver(s), designated as *Smart Adapters*.



Fig. 1: Example of an installation of SensFloor under progress.

Several approaches can be found in the literature regarding capacitance measurement. For instance, the sensor plates can be part of oscillators, whose resonance frequency is shifted when conductive objects are near the plates [7]. Another approach relies on the level of charge that can be stored in the capacitor when a power source is connected [6]. With SensFloor, each of the sensor plates is treated as an ideal capacitor, and the time it takes to charge it to a given percentage of the voltage supplied is measured. Capacitance, and consequent object distance, is extrapolated from the measurement [2].

The system also features a drift compensation mechanism and an auto-calibration method to compensate for permanent conductive materials placed upon itself, such as furniture. SensFloor can detect a human foot hovering up to a few centimeters over the floor.

SensFloor provides a platform to detect persons' activity, featuring a broad range of possible applications, while remaining completely transparent to the user. Some examples include the home automation and security domains, where it can be used for environment control and intelligent alarm systems, and *Ambient Assisted Living* systems, improving the quality of life and independence of senior citizens, who wish to live in their own home as long as possible.

### III. POSITIONING AND TRACKING

In this section, we describe the use of the SensFloor technology to extract information about the position of multiple users, from the raw sensor data coming from the floor. We are able to tell the number of users over of the installation, as well as to individually track them through Kalman filtering [8].

#### A. Cluster extraction and classification

In order to estimate the position of a person standing or walking on the floor, we need to relate active pads to footsteps on the floor. Despite the SensFloor's triangular pads being designed to match the average human foot length, it is highly unlikely that only one pad will be active with each footstep taken. Thus, it becomes necessary to group nearby active

pads, forming clusters. A straightforward approach would be to assume that the three surrounding pads of an active one (three edges of the triangle) form a cluster. However, albeit the last example being the most common scenario, a foot may also lie in a different fashion. Figure 2a shows three cases of footsteps which activate other nearby pads that are not concurrent (blue triangles), but still belong to the one footstep. As such, Figure 2b shows all the possible neighboring pads (light gray) that one footstep may also activate.

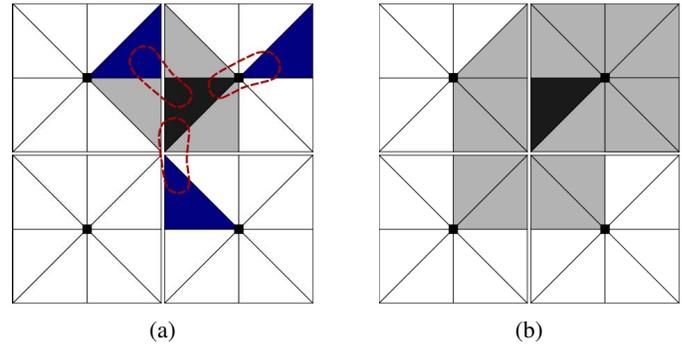


Fig. 2: Cluster identification from different footsteps placement on SensFloor.

By defining clusters as such, we can assume that each standing or walking person can only generate one or two clusters, depending on stride length and floor resolution. In this way, a simple method to classify clusters, thus associating them with a person, is to consider the nearest neighbor. That is, if a cluster has neighbors within a given distance,  $d$ , the closest one is grouped, and the two represent the individual.

Figure 3 shows an example with three clusters. Consider cluster (b). Here, cluster (a) is within the immediate neighboring area (delimited by  $d$ ), whilst (c) lies outside. Therefore, we associate one person [P1] with clusters (a) and (b), and another [P2] with cluster (c), despite the latter being generated by two footsteps instead of just one. The position of clusters, in the  $(x,y)$  coordinate system, and the position of persons within two associated clusters, are taken as the average distance between the active pads and average distance between clusters, respectively. The centroid of the triangular shaped pads is used as the pads' position relative to the module.

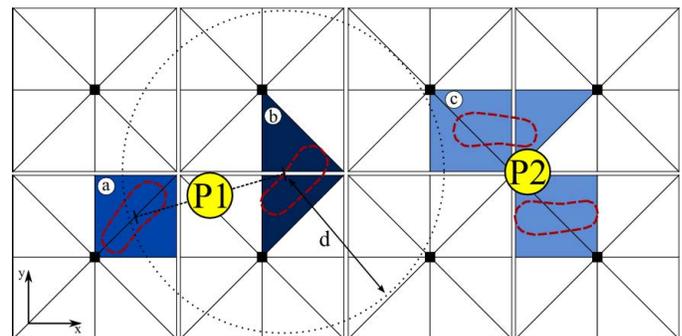


Fig. 3: Object classification from clusters.

## B. Tracking

Tracking, in this application, consists of being able to locate a moving person in time. In the case of our system, tracking is quite challenging, considering that a walking person can have either one or two feet in contact with the floor, depending on the phase of the step. Furthermore, multiple persons can be moving on the floor simultaneously, increasing the complexity and leading to an association problem as well, that is, which classified position corresponds to each person being tracked. Moreover, sensor signals from the SensFloor are noisy, making the position of classified persons “jump”. To overcome these issues, we employ the popular Kalman filter approach, where we assign one estimator to each person being tracked.

Since its introduction in 1960 by R.E. Kalman [8], the Kalman filter has been subject to extensive research, becoming a widely used tool when dealing with noisy systems. It is composed of a set of equations that provide a recursive approach to estimate the state of a process, giving good results even if the exact model of such process is unknown [9]. In other terms, it tries to find a compromise between the predicted state and noisy measurements. It can be found in several applications, including object tracking, navigation and computer vision applications [10].

A simple *constant-acceleration* linear model [11] is used for each tracker. Inclusion of acceleration in the state vector allows for a better response, considering the fact that a user’s movement is more erratic when compared, for instance, with an airborne projectile being tracked.

The resulting positions extracted from the classifier,  $(x,y)$  (see previous section), are used in the measurement input vectors for the filters. As stated before, we account for the presence of multiple individuals at a time by assigning one of these estimators to each of them. Since there are multiple estimators and multiple measurements, coming from the classifier, in each iteration, we consider the one closest to the last estimated position from a given tracker, as the new measurement input vector for that tracker. Cases where individuals walk too close to each other to be correctly differentiated from one another, however, represent a special occurrence. As such, we define four main events that affect the tracking system:

- *Assign* - when a person walks into the monitored area.
- *Delete* - when a person leaves the monitored area.
- *Merge* - when two or more subjects walk into the same region and cannot be individually located.
- *Separate* - when two or more subjects in the previous state (*merged*) walk away from each other.

The cases of *assign* and *delete* are straightforward, where an estimator is simply created or discarded, if the person enters or leaves the area, respectively. When starting to track a new subject, the filter is initialized with the first position extracted from the floor measurement.

The *Merge* and, consequential, *Separate* cases only affect the parameters of the filter. We consider two or more objects to be merged if they are estimated within a given distance from

one another. When merged, the measurement noise component of the filters is greatly increased, making so that the estimated position relies much more on the predictive component as opposed to the measurements.

Using Kalman filtering for tracking, in this application, provides smoother user trajectories, as well as short-term position prediction, both in the individual’s step-to-step motion and in cases of users walking close to each other (*merged*).

SensFloor can serve as a useful tool to track the activity of individuals in a residence, for instance, in *Ambient Assisted Living* (AAL) applications [19]. By recording the location (and trajectory) of a given user throughout the day, higher level behavioral models can be built to represent typical activity levels and detect abnormal situations.

## IV. USER IDENTIFICATION

As previously mentioned, user identification plays a vital role when it comes to context for smart systems. In this section, we describe how we perform footstep detection on small user-bound devices, and show a first approach to achieve such identification, for multi-user scenarios, by correlating these temporal step signals from the individual pedometers with data from SensFloor. These devices also serve as an additional activity data source, in the form of footsteps, for areas not covered by the floor.

### A. User-bound pedometer

A device able to detect human footsteps is commonly known as a pedometer. Most modern pedometers are based on widely available MEMS (Micro-Electro-Mechanical Systems) inertial sensors [13][14].

The EZ430 Chronos Watch from Texas Instruments [15], which is based on the CC430F137 microcontroller and features a 3-axis configurable accelerometer (VTI CMA3000), is an example of an embedded platform, which pairs this type of sensors with a processing unit, that can be used for step detection. Furthermore, it also includes an RF transceiver (similar to the ones found on SensFloor modules), allowing for wireless data transmission. As such, we use this device as our pedometer, where step detection is performed online, with RF messages sent to a central receiver. Moreover, by implementing our message protocol and assigning unique IDs to each device, these are transparently integrated with the floor network, making so that the data coming, both from the floor and from the pedometers, can be logged and processed in the same central application. Each time the user takes a step a message is sent to the receiver.

The accelerometer on the device is configured with a sample rate of 100 Hz and a range of  $\pm 2g$ . A band-pass filter is used on the norm of the 3D acceleration vector, considering a typical human walking frequency of 1 to 3 Hz. Albeit being available as a watch, we use it attached to the user’s hip, resulting in a higher detection rate and lower implementation

Regarding the step detection algorithm, a simple peak detection approach is implemented, where peaks on the filtered acceleration signal, above a certain threshold, represent a step and generate an RF message for the receiver (Figure 4).

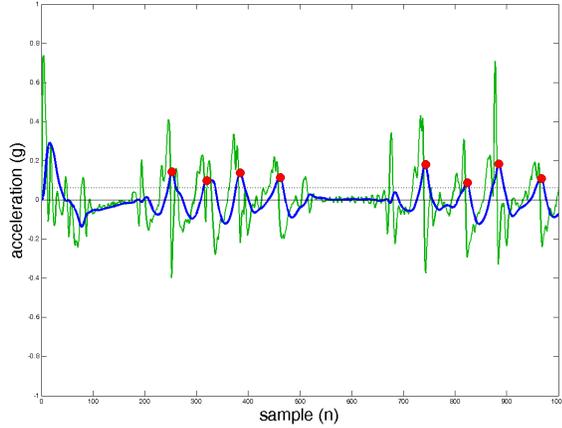


Fig. 4: Footstep detection performed on the acceleration data. The green and blue lines are the norm and filtered accelerations, respectively. The red dots represent the steps detected.

### B. Data fusion

Despite being able to account for the location of a user, detecting the timing of footsteps on SensFloor (independent of tracking) proves quite challenging. For instance, varying level of capacitance upon contact, depending on floor cover and user's shoe; signals generated by a hovering foot; and *heel-to-toe* step motion activating different sensor plates.

A low pass filter and a configurable threshold are used to detect the footstep timing, while the irregular *heel-to-toe* stepping motion is dealt with by employing a temporary mask to ignore nearby sensor plates (see Figure 2b). Since in this first approach we are only interested in the timing of footsteps for identification, these other signal features from the floor are filtered out (*hovering* and *heel-to-toe*). Nevertheless, such features, distinctive to capacitive floors, can be used in the future for a walking behavior analysis. In the end, each step detected in a plate is mapped to the plate's position and associated with the closest human being tracked.

Regarding the correlation between both step signals, the temporal displacement between steps from the floor (for every human tracked) and steps from users' devices, is used as the basis for the identification algorithm. The exact timing of every step can not be extracted from both step detection algorithms (due to delays caused by the online filtering and loss of RF messages). Thus, a vector is created for each of the detected steps on SensFloor, which encodes the probability of it being correspondent to steps from the users. The following figure shows the temporal progression of such a footstep detected on SensFloor, with several device steps close to it, in time.

Here,  $t_{SF}$  represents the time of a step, generated by a given human being tracked, and  $t_{1..3}$  are the times of steps from the user-bound pedometers, within a time window,  $\pm\Delta t$  (250 ms), around  $t_{SF}$ . Device steps closer in time to the floor step have a higher weight,  $\alpha_k$ , than ones further away (1) ( $\alpha_k = 0$ , for

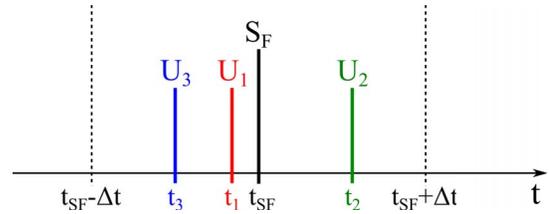


Fig. 5: Timing diagram depicting a step on the floor, associated with a given tracker, and steps from the pedometers.

devices without steps within the time window).

$$\alpha_k = \left(1 - \frac{|t_{SF} - t_k|}{\Delta t}\right) \quad (1)$$

Nonetheless, floor steps with fewer device steps within the time window should be considered less ambiguous, thus with higher probability of belonging to a given user. Ultimately, if only one device step lies within this window, it should have maximum weight, regardless of time between both. As such, (2) gives the final individual weights for each device, which compose the probability vector,  $\vec{W}_n$  (3), for a given floor step.

$$\omega_k = \frac{\alpha_k}{\sum_{i=1}^K \alpha_i} \quad (2)$$

$$\vec{W}_n = [\omega_1, \omega_2, \dots, \omega_k] \quad (3)$$

To associate the human being tracked with a user (device), an average is taken from the history of the probability vectors of each step. The user with the maximum value in the resulting vector identifies the human (4). Furthermore, by averaging all the steps, each consecutive one taken counts less for the overall identification algorithm, with the step history becoming more relevant.

$$U_m = \max \left( \frac{\sum_{i=1}^N \vec{W}_i}{N} \right) \quad (4)$$

Nevertheless, cases where two or more individuals have the same most probable user resulting from the probability vectors may occur. In this case, the one with higher probability of being this user wins the competition. However, the total number of steps taken should also come into play. For instance, consider two persons stepping onto the floor almost at the same time, one stops after taking a single step and the other continues to walk, and both have the same most probable user. In this scenario, the individual who stopped may have a higher probability of being the user than the one who continued to walk, since the latter is averaging all the steps taken. As such, the more steps are taken by the individual, the more likely he/she should be to win the competition (5).

$$U = \max \left( \frac{U_m * N_m}{N_{total}} \right) \quad (5)$$

The next section describes the experimental setup and some test scenarios using an area covered with SensFloor and three Chronos devices as pedometers.

### V. EXPERIMENTAL SETUP

We equipped a corridor (6m x 2m), within our company, with SensFloor. The installation featured 24, 2x1 sensor modules (1m x 0.5m). The approach described was implemented in a MATLAB application, which also included logging and video recording capabilities for ground truth analysis.

We collected data during a week, in normal office conditions, with this setup and with three users carrying the devices. Each time someone stepped on the floor, the camera started recording the event. We selected events with more than two steps on the floor for analysis, resulting in 453 events in total. However, due to the nature of the experimental setup (corridor), the vast majority of these consisted of only one person walking over the floor at a time (with/without pedometer), making up for 398 events, with the remaining 55 having two or more persons. Table I shows the results.

	Type	Count	User Identified	False Pos.
One	With device	190	187	3
	Without device	208	175	33
Two+	With device	14	14	2
	Without device	10	10	2
	Both	31	22	20

TABLE I: Identification results from the events.

The system correctly identifies the user in almost all single cases (with pedometer) walking over the floor. Individuals without pedometers are identified as unknown. However, more false positives emerge in the latter case, due to signals coming from pedometer-carrying users, walking near the floor, being wrongly associated with the ones walking over it. Events with two or more individuals are divided into three cases, depending on whether or not they carry a pedometer: all with, all without, and both. For these events, we consider if at least one individual is correctly identified (user or unknown), and if at least one is wrongly identified (false positive). In the last case, the system shows poor performance (large number of false positives), with unknown individuals flagged as users. Seldom events with more than two individuals walking at the same time over the floor were recorded. Even more, in such events, the individuals were often too cluttered together, such is why the events were divided only into two groups.

The cases of single users over the floor were also used to test the footstep detection algorithms. Table II shows the detection rates. The lower detection rate on the floor is due to the smaller resolution of SensFloor used (1m x 0.5m).

	Total	Detected	False Pos.	Rate
Devices	1621	1465	24	90 %
Floor	3086	2357	98	76 %

TABLE II: Footstep detection rates on devices and floor.

Next we show two additional test scenarios, using the setup described, with three users carrying the pedometers.

Figure 6 shows the first scenario, where two users walk in opposite directions on the corridor. Here, the left and right panels represent snapshots of the video and the application’s map representation of the floor, respectively. In the latter, the blue sensor plates are the clusters detected, and the square shapes (O1, O2, ...) are the objects being tracked, at their estimated positions. Furthermore, identified users are represented with different colors. (a) shows the moment when both users initially step on the floor, and are identified as unknown individuals (yellow). In the next snapshot, (b), each of them is now correctly associated with their specific devices (green and blue). The users continue on their path, remaining with the correct identification after crossing each other (d).

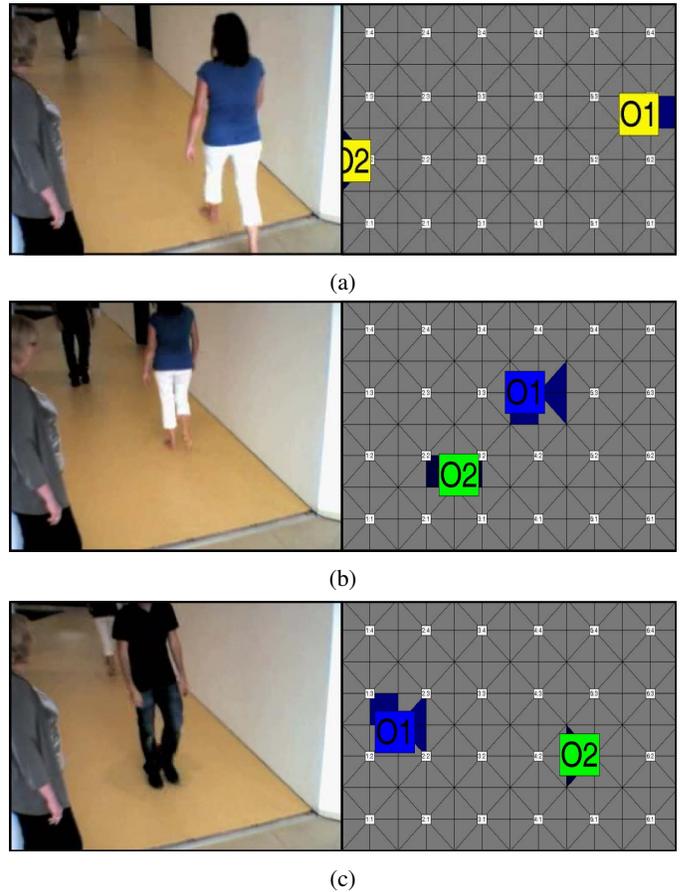


Fig. 6: Two users walk in opposite directions over the corridor.

In the next scenario, Figure 7, the three users walk in the same direction on the corridor. Two users start side by side, and walk at a similar pace, whilst the third one joins afterwards. (a), again, shows the initial steps taken by both users, with trackers’ assignment. Despite the step signals timing from these two users being close, the identification algorithm converges to the correct IDs (b). In (c), the third person steps on the floor and is correctly identified (cyan).

This approach does not guarantee correct user identification

in all cases. In addition to footsteps being missed, both in the pedometers and in the floor (especially with lower sensor resolutions or stride lengths), exact timing is not available. However, we try to mitigate it by basing the identification algorithm on the history of the steps taken. Nevertheless, small areas covered by SensFloor, in which the users only generate a small number of steps, can easily lead to false identification.

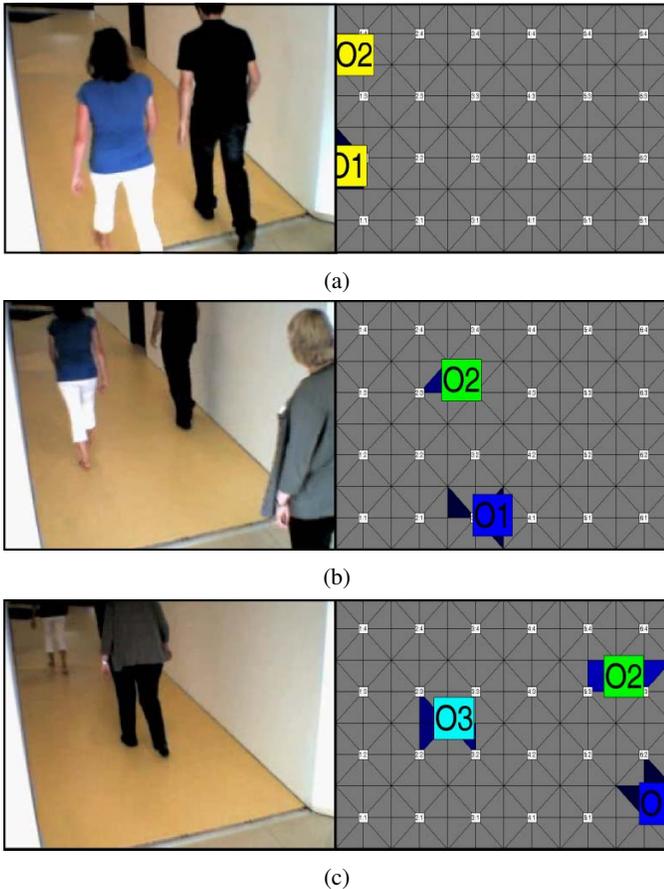


Fig. 7: Three users walk over the corridor at the same time.

## VI. CONCLUSIONS AND FUTURE WORK

In this work we have demonstrated the use of SensFloor in human localization and tracking. Cluster extraction from the floor sensor data is based on footstep placement on sensor plates, and serves as ground for object (human) localization. Furthermore, we perform multi-object tracking by means of Kalman filtering. Such allows, not only to get smoother trajectories from the noisy floor data, but also to anticipate the step-to-step location of a given human, as well as to temporarily address cases of humans walking close each other.

Moreover, we use small user-bound pedometer devices, integrated with the floor sensor network, as an additional footstep source, paired with the floor data in order to identify users. Albeit relying on user-bound devices, this identification allows two or more individuals to share the same smart environment, while being individually tracked and providing a mean for user-specific assistance and custom interfaces.

In the future we aim to test our system in larger areas, and for longer periods of time, such as in an AAL application, with an entire residence equipped with SensFloor. Furthermore, we aim to investigate the number of users that the system is able to track and identify within a given place, as well as the impact of different floor resolutions. Moreover, the integration of the system with other types of indoor localization systems (like smartphone-based pedestrian dead-reckoning [12]) can serve as an additional source of data for the identification algorithm.

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