# Sensing floors for privacy-compliant surveillance of wide areas

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## Abstract

*Surveillance systems can really benefit from the integration of multiple and heterogeneous sensors. In this paper we describe an innovative sensing floor. Thanks to its low cost and ease of installation, the floor is suitable for both private and public environments, from narrow zones to wide areas. The floor is made adding a sensing layer below commercial floating tiles. The sensor is scalable, reliable, and completely invisible to the users. The temporal and spatial resolutions of the data are high enough to identify the presence of people, to recognize their behavior and to detect events in a privacy compliant way. Experimental results on a real prototype implementation confirm the potentiality of the framework.*

## 1. Introduction

Traditional surveillance systems composed by a network of visual sensors and one or more processing and storage nodes achieved an enormous diffusion, both in private and public spaces. Nevertheless, two major drawbacks still characterize vision-based systems. First of all, the complete coverage of wide areas is reached only using a redundant number of cameras. Placement constraints and the handling of occlusions due to furniture, objects and people usually impose the adoption of multiple views, especially in indoor environments. Furthermore, privacy issues strongly limited the usability and also the user acceptability of surveillance systems. Completely automatic infrastructures only mitigate the problem by storing and exploiting anonymised or aggregate data.

In this paper we propose a different approach to surveillance based on a sensing floor (see Fig. 1.a). Instead of optical images, the floor is able to generate a pressure image, where each pixel corresponds to a spatial portion of the floor and the pixel value is related to the pressure applied by people or object onto the floor itself. This result is obtained adding a sensing layer below the ceramic tiles. The solution proposed is cheap enough to allow the coverage of wide areas and the sensing elements do not change the design or the appearance of the floor. In addition, the data collected from the sensors do not contain identifying elements such as faces or biometric details, assuring an high respect of the user privacy. The sensing elements communicate with a processing unit through a wireless channel following a hierarchical network.

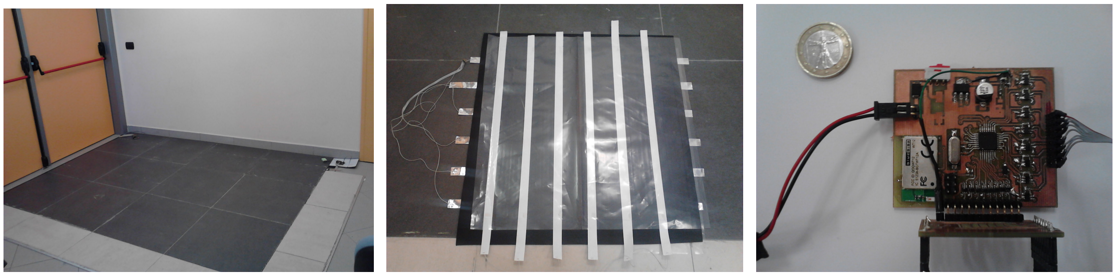
Several prototypes of sensing floors have been developed and proposed in the past. A representative subset of them is described in section 2. However, none of them fulfills all the following requirements, which are mandatory to generate a reliable solution to wide surveillance:

- *low cost*: the cost of the sensing elements should be comparable to traditional floors;
- *high scalability*: the sensors should be integrated into a hierarchical network, in order to allow the coverage of narrow rooms as well as wide areas;
- *transparent design*: for design issues, the sensing layer must be invisible to the users and the floor should appear like traditional floors;
- *high reliability and durability*: breakable and fragile elements should be avoided or limited to protected packages;
- *temporal and spatial resolutions*: they should be high enough to allow people detection and tracking, even in presence of multiple targets.

The preliminary experiments described in the paper shows the capability of the proposed sensing floor of detecting people and some basic behaviors such as falls, jumps and walks.

## 2. Related Works

Several prototypes of sensing floors for human-based action detection and identification have been presented in the past. The adopted sensors exploited different physical characteristics; among the others, the pressure as measurable



(a) (b) (c)

Figure 1. Pictures of the installed prototype. a) the floor, b) the contact stripes and c) the capturing board

quantity, and the proximity effect related with the electrical properties of a human body are the mainly used.

Yu-Lin Shen et al. [10] developed a distributed sensing floor using an optical fiber sensor. Its spatial resolution was around 18cm. The described method is based on Brillouin Optical Correlation Domain Analysis (BOCDA) technology, which detects the strain deviation along a fiber caused by pressure events. Main drawbacks of the proposed system are the complexity of the equipment used to detect the Brillouin frequency shift and the lack of spatial scalability.

Raja Bose et al. [2] proposed a distributed mechanism for observing human walking behavior by adapting phenomenon cloud detection and tracking techniques. The described mechanisms runs on a floor-based sensor network, consisting of a grid of piezoelectric force sensors embedded under residential floor tiles. Each tile has one force sensor attached to its central support. Piezoelectric sensors are expensive and need complex conditioning circuits, beside the integration of the sensors with tiles is not enough effective to manufacture a ready to be sold distributed sensing floors.

Miika Valtonen et al [13] described an unobtrusive two-dimensional human positioning and tracking system based on a low-frequency electric field. The capacitance between multiple floor tiles and a receiving electrode is measured. The method is based on the fact that humans well conducts a low-frequency signal. The proposed method does not provide any information related with the human weight; it is not possible to detect any kind of non conductive objects, regardless of the weight; finally the conditioning circuits are very complex.

Lee Middleton et al. [5] developed a prototype of a floor sensor mat as a gait recognition system. The sensor consists of individual switches arranged in a separated pair of wires by foam a deformable material. The design shows simplicity and scalability even if switches do not provide a response commensurate with the strength of the applied force.

Chen-Rong Yu et al. [15] proposed a localization system to accurately estimate human position. It performs single person and multiple people tracking in a home environment. The Condensation algorithm is exploited to locate residents' position via multi-camera and sensory floor approaches.

Domnic Savio et al [9] developed a smart carpet that can be laid on the floor. 180 capacitive binary sensor nodes are embedded in 240 cm by 200 cm smart carped. The sensor set forms a self-organizing sensor network. To identify the footstep, clustering algorithms based on Maximum Likelihood Estimate and Rank Regression have been applied. The proposed approach is scalable and commercially viable even if the binary nature of the embedded nodes does not provide a response commensurate with the applied weight.

In the work by Prashant Srinivasan et al. [12] a portable high-resolution pressure sensing floor prototype able to detect pressure information about the human interaction with the system is described. The pressure sensing floor consists of several sensor mats; each of them is composed of a 42x48 grid of pressure sensors with size of 48.8 cm x 42.7 cm. The sensor elements of the mat are made using a pressure sensitive polymer between conductive teaks on sheets of Mylar. The sensor elements change the resistance with the applied pressure.

Jan Anlauff et al. [1] presented a prototype of a floor surface based on sensing elements made out of conductive black art paper. The sensing elements are grouped into modules forming a grid of resistors able to measure quasi-static forces. The proposed approach is a low cost alternative for spatially resolved tactile sensing. The employed signal conditioning system is based on the matrix arrangements of the sensing elements but the proposed solution suffers of mutual interference between different sensors in the matrix.

Finally, in the work by Rishi Rajalingham et al. [7] a probabilistic approach to the tracking and estimation of the lower body posture is presented. Their sensing floor has limited sizes, it is not easily scalable and commercially viable. It employes off the shelf resistive force sensors. It consists of a 66 array of rigid tiles, 30 cm on each side. Tiles are equipped with four resistive force sensors, which are located at the corners. An array of six small-form-factor computers is used for data processing.

## 3. System Architecture

The system architecture is composed of four main entities: the sensors, the capturing boards, the communication network, and the processing unit.

The sensors are obtained by introducing a sensing layer below a commercial floating floor. The sensing stratum replaces the polymeric layer which is usually adopted to cobble surfaces using floating floors. The sensors are located in a regular grid with a spatial resolution of about 10 cm and they are grouped in sets (called *Base Nodes - BNs*) composed by 64 or 128 items.

A board equipped with a 8-bit micro controller (ATMEGA328) is connected to each Base Node. The sensed values are sampled and digitized at a constant frame rate and sent via Blue-tooth to a processing unit for their analysis (e.g., people tracking, object detection, and so on). A hierarchical communication network is also proposed for scalability reasons and it can be used when the number of BNs exceeds the capabilities of a single processing unit.

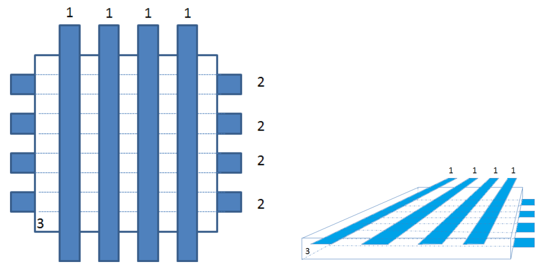
Differently from other solutions which have been proposed in the past [6, 12, 8], each sensing element looks like a normal floating tile. Thus, it inherits some key advantages: low cost, easy tile replacement, high resilience, high stability, feasible relocation of the floor. The proposed approach allows to make wide sensing areas at affordable costs. Some pictures of the prototype floor and the embedded board used to capture and transmit the data are reported in Fig. 1.

### 3.1. Base node sensors

The invisibility to the user is one of the key requirements of the system. To this aim, we started from a commercial paving technology, called floating floors. A floating floor does not need to be nailed or glued to the sublayer and thus it might be constructed over a sub-floor or even over an existing floor. It consist of a polymeric, felt or cork layer holding up a laminate floor. Drowning commercial pressure sensors such as FSR or piezoelectric elements into the padding layer allows to reach very high performances in terms of measurement precision and reliability. However, the solution becomes too expensive and thus unfeasible in wide areas.

We propose to replace the traditional polymeric layer with a sensing element made using a sandwich structure (see Fig 1.b and Fig. 2). A conductive polymer (3) is put between aluminum stripe electrodes, lengthwise (1) and crosswise (2). The sensor grid is composed of 16 rows and 8 columns, which produce 128 sensing units for each 1.28 square meters.

When a pressure is applied on the top of the tiles, the rough surface of the conductive rubber is compressed onto the electrodes surface [14]. As a result, the contacting area




(a) (b)

Figure 2. Schema of the sensing layer under the floor. Row and columns of conductive stripes create a grid of virtual sensors

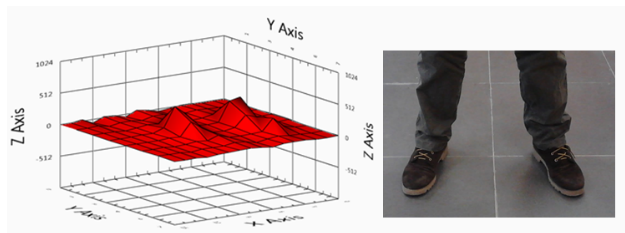



Figure 3. Picture of a person standing on the sensing floor and the corresponding captured values

| Item | Value |
|---|---|
| Polymer thickness | 2.5mm |
| Distance between stripes | 10cm |
| Number of lengthwise stripes | 8 |
| Number of crosswise stripes | 16 |
| Surface Resistance | $1.0 \cdot 10^5 \Omega/cm^2$ |
| Volume Resistivity | $1.0\text{x}10^4 \Omega/cm^3$ |

Table 1. Physical characteristics of the proposed floor

between rubbers and electrodes is increased whilst the resistance between them is proportionally reduced. The resistance at each cross is acquired using the board described in section 3.2.

Finally, we exploited very slim ceramic tiles for the higher layer. The tiles are 600mmx600mm large and thin enough (4.5 mm) to allow the sensing elements below them to capture the presence of walking people. In Figure 3 the picture of a standing person and a graph plotting the corresponding sensor values are reported. The two feet are correctly distinguishable, even if the ceramic tile partially distributes the person weight over all the sensor elements below. Some mechanical and electrical characteristics of the sensing floor are summarized in Table 1.

### 3.2. Capturing board

Each Base Node is equipped with a capturing board which measures the electric resistance at each grid cross, digitizes and transmits the values using a specific protocol. In Figure 4 the block diagram of the electronic

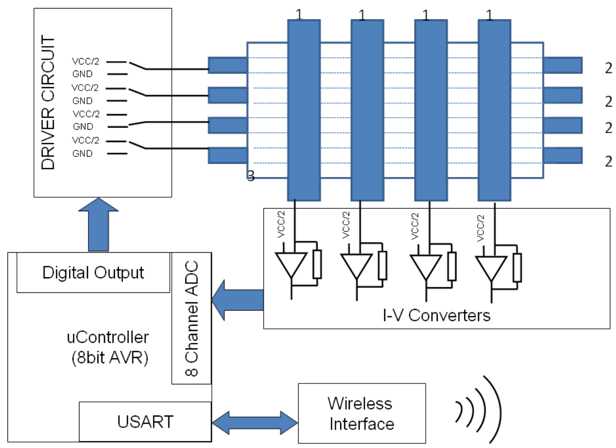



Figure 4. Block diagram of the capturing board

part is shown. The scanning method is designed to avoids measurements errors; in particular the zero potential method[11] is adopted. A ground voltage is applied to one row (1) at a time, and the other rows are instead polarized to $\frac{VCC}{2}$. Current-to-Voltage converters are connected to all the columns (2). All the columns are pre-charged to $\frac{VCC}{2}$, the same voltage of the unselected rows. This configuration avoids measurements errors due to leak resistance between sensor points. Output of I-V converters are digitized by ADC converter of the micro-controller (Tmega328 AVR 8 bit RISC architecture from ATMEL). The scanning time for each element can be set in a range from 7.8ms to 0.17ms, reaching a global scanning rate between 1 and 44 Hertz. The frames are sent to the processing unit which runs the system application through a wireless communication interface.

### 3.3. Communication Network

The number of base nodes can freely grow depending on the area to cover. A hierarchical communication network has been developed to obtain a high degree of scalability. In the most general case, data sensed by the base nodes are transferred through different levels of gateway — connected with different types of network — toward the central processing unit (Figure 5). For example, base node sensors use wireless communication to fastener and facilitate the floor installation, while top level channels may use wired links to increase the bandwidth and the communication distance.

BaseNodes (BN) are equipped with a single radio module; instead, two radio modules are embedded in Intermediate Gateways (IGW) and Main Gateways (MGW). When BNs are not involved in communication or sensing activities, they must go into a sleep state to save energy: sensors are turned off and the microcontroller is placed in a power saving mode. In this case, BNs are woken up by the communication line. Data can be transmitted only when an event is detected to save additional energy. In this case the micro-controller can be switched to the power saving mode and the working mode based on the signals from the sensors. Every BN should be identified by a logical address to enable unit-to-unit communication and to identify each unit in the whole system. Sensor Network of Figure 5 is the general architecture where all communication levels are present. These configurations are suitable for wide areas, likes stations, airports and public places. Four communication channels are available:

1. BN to BN (Green Arrows). Channel for synchronization and data collection with low data rates and near locations between BNs;

2. BN to IGW (Red Arrows). Channel used by IGW to collect data from different BNs. Data rates depends on the Application, that defines the frame rates, and numbers of BNs;

3. IGW to MGW (Blue Arrows). As point 2, with MGW in place of IGW and IGW in place of BN but with data rates much greater than others levels;

4. MGW to Application (Black Arrows). It's the last step of system communication. Application interface can be every type of computers or portable devices. Data rates can be very high, so a standard high data rates wireless protocol must be used, like WiFi.

The Hardware Protocol has been uniquely defined for all the network levels. Using the AMaGWI (Application-Main GateWay Interface) protocol, a device of the network can be viewed like a USB Hub, with downstream and upstream ports: MGW and IGW can be defined as AMaGWI Hub. Instead, the BN has AMaGWI Hub functions and sensing capabilities.

The custom AMaGWI protocol has been set general enough to be implemented at every level of communication. The protocol requires the identification of each sensor, base node and Gateway with a specific ID. Both the stream and On-Demand transmission schemes are available. In both cases, mask commands can be used to select and update a sensor subset only. Selective and sampling strategies can be implemented at application level for energy saving or bandwidth reduction policies.

### 3.4. Processing Unit

The processing unit represents the higher level of the network and collects, processes and stores the data from all the sensors. Thanks to the regular distribution of the sensors below the floor, the processing unit firstly generates a "floor image", in which each sensor corresponds to a pixel and the spatial neighborhood relations are preserved. Subsequent

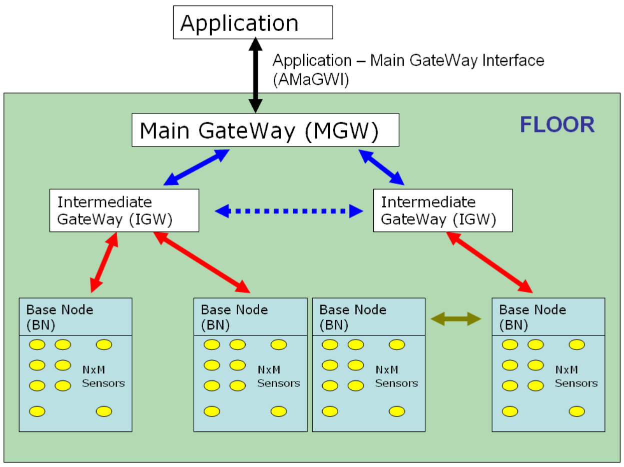



Figure 5. Schema of the hierarchical communication network

sensor samples are handled as frames in a video, allowing the adoption of common image and video processing techniques to extract high level information from the sensor data as described in Section 4.

## 4. People detection and behavior analysis

As above mentioned, the detection of people and the further classification of their behaviors are provided using common video processing and analysis techniques. The recognition of the people behavior using video cameras has been deeply addressed in the past using spatio-temporal descriptors[4, 3]. From video sequences, spatio-temporal 3D patches are extracted selecting rectangular regions and aggregating successive frames cropped on them.

To simulate the same approach, we selected a single tile of the floor and we collected the NxM values of the sensors below it during a short time interval (2 seconds, corresponding to 20 frames). The obtained matrix $I(x, y, t)$ is processed in order to generate a feature vector for the classification step. We adopted a feature vector composed by aggregated measures which do not depend on the spatial and temporal position of the selected event within the analyzed block. In other words, the feature vector does not depend on the absolute position of a person within the analyzed floor tile. Let $M(t)$ be the mean value of $I$ at time $t$, $x(t) = \sum_{x=1}^{M}\sum_{y=1}^{N}(x \cdot I(x, y, t))$ and $y(t) = \sum_{x=1}^{M}\sum_{y=1}^{N}(y \cdot I(x, y, t))$ the coordinates of the barycenter $b(t) = (x(t), y(t))$. $C(t)$ is the covariance matrix of the vectors $\{x, y, I(x, y, t)\}$. Let be $\{e_1(t), e_2(t), e_3(t)\}$ the three eigenvalue of the matrix $C(t)$. The features $\Phi = \{\phi_1, \ldots, \phi_{15}\}$ are extracted as average, min or max of the previous defined values as follows:

| Class | Description |
|---|---|
| class 0 | Absence of people or weights on the floor |
| class 1 | Presence of a standing person on the floor |
| class 2 | Presence of a walking man on the floor |
| class 3 | Presence of a jumping man on the floor (single jump) |
| class 4 | Presence of a lying person on the floor |
| class 5 | Obstacle / fixed object |

Table 2. Description of the considered classes.

$$\begin{aligned}
\phi_1 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=1}^{n} M(t) \\
\phi_2 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=1}^{n} (M(t) - \phi_1)^2 \\
\phi_3 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=2}^{n} |M(t) - M(t-1)| \\
\phi_4 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=2}^{n} (|M(t) - M(t-1)| - \phi_3)^2 \\
\phi_5 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=2}^{n} ||b(t) - b(t-1)|| \\
\phi_6 &= \tfrac{1}{n} \cdot \textstyle\sum_{t=1}^{n} (||b(t) - b(t-1)|| - \phi_5)^2 \\
\{\phi_7 \ldots \phi_9\} &= \tfrac{1}{n} \cdot \textstyle\sum_{t=1}^{n} \{e_1(t) \ldots e_3(t)\} \\
\{\phi_{10} \ldots \phi_{12}\} &= \min_t \{e_1(t) \ldots e_3(t)\} \\
\{\phi_{13} \ldots \phi_{15}\} &= \max_t \{e_1(t) \ldots e_3(t)\}
\end{aligned} \tag{1}$$

$\phi_1$ and $\phi_2$ are the mean and variance of $M(t)$ over the temporal interval; $\phi_3$ and $\phi_4$ are the mean and variance of the $M(t)$ variations. $\phi_5$ and $\phi_6$ take into account the movement of the barycenter. Finally, $\phi_7$ to $\phi_{15}$ evaluate the average, the minimum and the maximum three eigenvalues of the covariance matrix.

The obtained features have been provided as input to a set of supervised classifiers trained to detect the presence of a person or a fixed object on top of the tiles. If a person is detected, the same feature vector is evaluated to further classify its posture or action. We developed a collection of Randomized Trees classifiers for both the tasks. As a proof of the system capabilities, in section 5 we provide the classification results on the classes reported in Table 2, where binary classifiers have been trained and tested to better highlight the discriminability of each class against the others.

## 5. Experimental evaluation

Our experimental environment consists of a prototype sensing floor which implements all the described elements. We acquired data from a selected portion of the floor at a scan rate of 10 Hz. We trained three classifiers using the proposed feature set, which have been extracted from 100 acquisitions of 2 seconds for each class listed in Table 2.

In addition to the results obtained with Random Tree classifiers, we evaluated the system performances using linear Support Vector Machines (SVM) and Nearest Neighbor classifiers. The classification accuracy is computed adopting the leave-one-out methodology and applying the one-against-all configuration for the binary classifiers. Table

| | SVM | Random Trees | N.N. |
|---|---|---|---|
| class 0 vs all | 98.8% | **99.8%** | |
| class 1 vs all | 95.8% | **92.6%** | |
| class 2 vs all | 94.4% | **98.0%** | 85.8% |
| class 3 vs all | 92.0% | **96.2%** | |
| class 4 vs all | 97.6% | **98.4%** | |

Table 3. Accuracy results using Support Vector Machine

| | Accuracy |
|---|---|
| SVM (class 1 vs class 5) | 89.5% |
| RF (class 1 vs class 5) | 98.8% |
| NN (Euclidean) | 85.8% |
| NN (Manhattan) | 85.6% |

Table 4. Accuracy results of class 1 vs class 5

3 shows the obtained results, highlighting a very promising accuracy using the Random Tree classifiers (average of 97%).

In order to evaluate the efficacy of the selected features to discriminate a standing person (class 1) from a fixed obstacle of similar size and weight, we introduced an additional class (class 5, hereinafter). To this aim, we tested the system on further 100 acquisitions from the selected region with the presence of a static object having a comparable weight. The accuracy of the three classifiers to discriminate between standing people and fixed objects are reported in Table 4.

## 6. Conclusions and Future Works

In this paper we proposed a new framework for the production of innovative sensing floors. Their low costs, high reliability and high scalability make the proposed solution very promising also from the commercial point of view, allowing wide installments in both private and public spaces. The intrinsic compliance with privacy issues and the complete transparency from the user perspective make more easy their acceptability. Preliminary tests on a laboratory prototype highlighted their sensing capabilities, which are high high enough to allow the detection of people and to classify their behavior. In the future, we plan to install a wider prototype to effectively test the scalability of the system as well as the capability of monitoring crowded areas.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