HAL
open science

Localisation of humans, objects and robots interacting on load-sensing floors

Mihai Andries, Olivier Simonin, François Charpillet

To cite this version:

Mihai Andries, Olivier Simonin, François Charpillet. Localisation of humans, objects and robots interacting on load-sensing floors. IEEE Sensors Journal, 2016, 16 (4), pp.1026-1037. 10.1109/JSEN.2015.2493122 . hal-01196042v2

HAL Id: hal-01196042

https://inria.hal.science/hal-01196042v2

Submitted on 29 Oct 2015

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

Localisation of humans, objects and robots interacting on load-sensing floors

Mihai Andries, Olivier Simonin, François Charpillet

***Abstract*—Localisation, tracking and recognition of objects and humans are basic tasks that are of high value in applications of ambient intelligence. Sensing floors were introduced to address these tasks in a non-intrusive way. To recognize the humans moving on the floor, they are usually first localized, and then a set of gait features are extracted (stride length, cadence, pressure profile over a footstep). However, recognition generally fails when several people stand or walk together, preventing successful tracking. This paper presents a detection, tracking and recognition technique which uses objects' weight. It continues working even when tracking individual persons becomes impossible. Inspired by computer vision, this technique processes the floor pressure-image by segmenting the blobs containing objects, tracking them, and recognizing their contents through a mix of inference and combinatorial search. The result lists the probabilities of assignments of known objects to observed blobs. The concept was successfully evaluated in daily life activity scenarii, involving multi-object tracking and recognition on low resolution sensors, crossing of user trajectories, and weight ambiguity. This technique can be used to provide a probabilistic input for multi-modal object tracking and recognition systems.**

***Index Terms*—Intelligent systems, Ubiquitous computing, Ambient intelligence, Home automation, Force sensors, Sensor arrays, Identification of persons**

I. Introduction

Ambient intelligence is a domain of research that explores how sensing environments can interact with their inhabitants. It requires the reconstruction of a model of the environment that is used for reasoning. In this context of model reconstruction, the localisation, tracking and recognition of objects and human beings in the supervised environment become important. Load-sensing floors were introduced to solve this problem in a non-intrusive manner [1] [2] [3]. The traditional way of recognizing humans was by first tracking them, extracting gait features and then identify them using clustering techniques [4] or Hidden Markov Models (HMM) [1] [2]. However, this type of recognition failed whenever the extraction of gait features became impossible. This happened when multiple users walked alongside, preventing the algorithm from correctly segmenting and tracking each of them on the floor.

This paper presents an object recognition approach which localizes and recognizes multiple objects simultaneously by analyzing the load they exert on the floor. As it does not extract gait features for recognition, it does not require fine tracking of individual persons inside a group. In contrast to clustering and HMM techniques, this new approach is based on the *multiple knapsack problem* [5], a combinatorial approach which uses information about object weight and size. It can be used to provide a probabilistic input for a multi-modal object recognition and tracking system. This technique was implemented in an ambient intelligence setting, where a non-intrusive load-sensing floor was used. The main drawback of this approach is its computational complexity, due to the sheer number of possibilities of correlating known objects to the observations made. However, this issue is classically solved using dynamic programming.

For our research experiments, we have designed a sensing floor prototype, which allows us to assess how this technology can be used for more advanced applications than those available today on the market. This also allowed us to overcome the drawback of the devices available off-the-shelf, which are not open and not designed for integrating new sofware. The floor has a modular design, being composed of load-sensing tiles, whose concept was described in [6].

The rest of this paper is organised into 6 sections. Section II presents the state of art in the domain of load-sensing floors. Section III introduces the load-sensing equipment used to experimentally evaluate our algorithm. In section IV, our load-data processing approach is exposed, with an emphasis on object detection, tracking, and recognition. Then, experimental results for the proposed algorithm are presented and analysed in section V. Finally, directions for future work are evoked in section VI.

II. Related work

The use of floor-sensors in ambient intelligence contexts began in the late 1990's, with projects like the ORL active floor [1] by Addlesee *et al.*, the Magic carpet [24] by Paradiso *et al.*, and the Smart floor [4] by Orr *et al.*, where they provided information for reasoning about the observed space. These floors were later integrated into smart environments, aimed at delivering assistance services like continuous diagnosis of users' health. These smart environments also integrated assistive robotic technologies with sensing networks. Examples include the Gator Tech Smart House made by the University of Florida [25], the Aware Home introduced by the Georgia Institute of Technology [26] [4], and the Robotic-Room system [27] [28] developed by the University of Tokyo.

M. Andries and F. Charpillet are affiliated to:
- Inria, Villers-lès-Nancy, 54600, France
- CNRS, LORIA, UMR 7503, Vandoeuvre-lès-Nancy, 54506, France
- Université de Lorraine, LORIA, UMR 7503, Vandoeuvre-lès-Nancy, 54506, France

O. Simonin is with the INSA Lyon CITI Lab., Inria Grenoble, Université de Lyon, 69621 Villeurbanne, France

M. Andries is supported by an Inria CORDIS grant within the Personally Assisted Living Inria Project Lab.

Table I: Methods for people identification using floor pressure

Scientific article	Year	Floor sensor	Major features	Classifier
Addlesee et al. [1]	1997	strain gauge load cells	Pressure profile over a footstep	Hidden Markov Model (HMM)
Orr et al. [4]	2000	strain gauge load cells	Key points from pressure profile	K-nearest neighbors (KNN)
Pirttikangas et al. [2]	2003	electro-mechanical film (EMFi)	Pressure profile over the entire floor during walking	HMM
Pirttikangas et al. [7]	2003	EMFi	Pressure profile over the entire floor during walking	Learning Vector Quantization (LVQ)
Yun et al. [8]	2003	pressure switch sensors	Compensated foot centers over 5 consecutive footsteps	Multi-layer perceptron (MLP)
Jung et al. [9]	2003	pressure mats	2D trajectories of center of pressure (COP)	HMM
Jung et al. [10]	2004	pressure mats	2D positional trajectories of COP	Hidden Markov Model, Neural Network (HMM-NN)
Suutala and Roning [11]	2004	EMFi	Features from spatial, frequency domain over a footstep	Distinction-sensitive Learning Vector Quantization (DSLVQ)
Suutala and Roning [12]	2005	EMFi	Features from spatial, frequency domain over a footsteps	MLP, LVQ
Middleton et al. [13]	2005	force-sensing resistor (FSR) mats	Stride length, stride cadence, heel-to-toe ratio	Not available (N/A)
Yun et al. [14]	2005	photo interrupter sensors	Compensated foot centers and heel-strike and toe-off time over 5 consecutive footsteps	MLP
Yun et al. [15]	2008	photo interrupter sensors	The left footprint pattern and the array of sampled transitional footprints over different combinations of 2 or 4 footsteps	MLP
Suutala and Röning [16]	2008	EMFi, same as [2]	Pressure and time features extracted from pressure profile over a footstep	MLP, Support Vector Machine (SVM)
Suutala et al. [17]	2008	pressure switch sensors	Single footstep: length, width, duration, number of pixels in the binary map, (min, max, mean, std) from the gray-level duration map; Between footsteps: stride, length, stride cadence	Gaussian Process
Qian et al. [18]	2008	FSR mats	2D trajectories of the Center of pressure, Pressure profile over time	Fisher linear discriminant (FLD)
Vera-Rodriguez et al. [19]	2009	piezoelectric force sensors	Geometric and holistic footstep data	SVM
Qian et al. [20]	2010	FSR mats	Mean pressure, stride length	FLD
Vera-Rodriguez et al. [21]	2010	piezoelectric sensor mat	Holistic pressure-time info	SVM
Yun et al. [22]	2011	photo interrupter sensors	Foot centers, heel-to-toe time, footprint geometric data	MLP
Vera-Rodriguez et al. [23]	2013	piezoelectric sensor mat	Fusion of time and holistic pressure info	SVM
Proposed method	**2015**	**strain gauge load cells**	**Weight over time**	**Knapsack algorithm**

Table I lists the floor sensing technologies capable of identifying people, updating the lists previously presented in [20] and [23]. The current main types of floor pressure sensing technologies are: capacitive sensors, piezoelectric sensors, piezoresistive sensors, strain gauge load cells, and photo interrupter sensors.

Being installed inside or under the floor, the load sensors perceive only a projection of the forces involved in human daily activities. This leaves space for ambiguities in tracking and recognition. Thus, whenever floor sensors seemed to be insufficient for any of the three tasks (localisation, tracking and identification), additional sensors were used in a multi-modal perspective to solve emerging data ambiguities. Sensing floors have been combined with radio-frequency identification (RFID) systems [29], pyroelectric infrared sensors [30], wearable accelerometers [31] [32], audio capture systems [33] and multiple cameras [34].

Load-sensing surfaces are also employed in biomechanical and medical laboratories. Examples include the GAITRite gait analysis system [35], which is an electronic walkway, and the Kistler force plates [36], which are used for sports and performance diagnostics, as well as for gait and balance analysis. Heller *et al.* used a force-measuring floor to investigate dynamic balance in humans [37], which is correlated to sport performance according to previous studies. Rajalingham *et al.* [38] used in-floor force-sensing to track the 3d body posture of pedestrians using Bayesian filters.

All the presented floors that are capable of human recognition extract a set of features for their tracking and identification task. Addlesee *et al.* [1] recognise humans using their pressure profile over a footstep as data, and using Hidden Markov Models as classifiers. They also mention the problem of interpretation of spread loads, when objects span several tiles on a modular floor. Orr *et al.* [4] use the vertical ground reaction force profile, as well as its derivates. These include the maximal load value during heel strike and during toe push-off, and the minimal load value recorded during the weight transfer from heel to toe.

Pirttikangas *et al.* [2] recognise individual persons walking on the floor using the pressure pattern of their gait and HMMs. Similarly, Middleton *et al.* [13] use the stride length, stride cadence, and time-on-toe to time-on-heel ratio and then recognise the subjects using a standard distance metric of similarity.

Qian *et al.* presented an approach to identify people based on features extracted from their gait [18]. They used a large area (180 square feet), high resolution (1 sensor per cm^2), networked pressure sensing floor which employed force-sensing

resistors [39].

Schmidt *et al.* [3] queried a database of known objects whenever a change was detected in the total weight of a scene, to see if there exists an entry that has the same weight as the absolute difference in weight detected. However, this process was neither probabilistic, nor could it detect simultaneous introductions or removals of objects from the scene.

Morishita *et al.* in [40] presented a high-resolution floor sensor composed of pressure switches, which provided binary information about the presence or absence of load on them. Its high resolution allowed to obtain sharp images of the surfaces in contact with the floor, such as footprints or shoe soles. It was suggested that an image processing software could regonize footprints.

Murakita *et al.* [41] performed multi-user human tracking on the VS-SS-F InfoFloor system using the Markov Chain Monte Carlo method. However, the employed floor sensors gave only a binary information about the occupation of its constituent tiles. Tracking would fail whenever two or more targets crossed their paths, generating tracking ambiguity. Attempts were made to solve this problem by fusing the information from the floor sensors with that from on-body acceleration sensors [32].

Savio *et al.* [42] identified footsteps on a *smart carpet* with integrated binary capacitive sensors, using clustering algorithms based on Maximum Likelihood Estimation and Rank Regression analysis. This allowed the extraction of user's trajectory.

Valtonen et al [43] presented a 2D human positioning and tracking system, which used a low-frequency electric field to locate humans on the floor. The system could only detect conductive objects, and did not provide information about the weight of objects.

Similarly, capacitive sensing floor mats capable of detecting and tracking objects in the environment were used by Braun *et al.* [44]. However, as this floor did not measure load forces, it could not recognize objects on its surface by their pressure profile.

Lombardi *et al.* [45] developed a tiled sensing floor, with tiles containing sensing stripes, and which was capable of tracking a walking human. They used a Randomized tree classifier to identify footsteps from the pressure signal. However, the floor did not implement any human recognition abilities. It is worth mentioning that they treated the floor pressure data as if it were an image.

Shen and Shin [46] developed a floor that uses an optical fiber sensor. It employs Brillouin Optical Correlation Domain Analysis (BOCDA) to calculate the location and the stress on the sensor. The floor was able to track two persons simultaneously. However, no identification abilities were developed or reported.

Yun *et al.* worked on several sensing floor prototypes [8] [14] [15]. Their latest prototype, the UbiFloorII [22], uses an array of tiles equipped with photo interrupter sensors. It uses multilayer perceptron networks to identify individuals based on the extracted features (stride length, foot angle, heel strike time, etc.).

Vera-Rodriguez *et al.* described a high-resolution pressure-sensing floor, which employs piezoelectric sensors mounted on a printed circuit board, and placed under a conventional mat [21]. The authors extracted the ground reaction force of footsteps [21] and their footprints [19], and performed human recognition using a Support Vector Machine. Recognition was performed using a database of 120 known people, the largest database to that date.

Lee *et al.* [47] presented a network of force-sensing resistors that can track users and allow them to interact with the smart environment by tapping the floor, onto which a visual interface is projected. Similarly, Visell *et al.* [48] used a tiled load-sensing floor as a human-computer interface, where an image of the interface is overlayed on the floor, on which users can press virtual buttons with their feet. The Active Gaming company proposed the pressure sensitive Lightspace Floor [49], which is an interactive gaming platform combining pressure sensors with LEDs for visual feedback.

More recently, sensing floors products like the SensFloor [50] (a floor network of capacitive proximity sensors), Capfloor [44] (a network of capacitive sensors), and FloorInMotion [51] started being commercialised by companies, mainly for the senior care industry. An innovative energy harvesting sensing floor has also been proposed in [52].

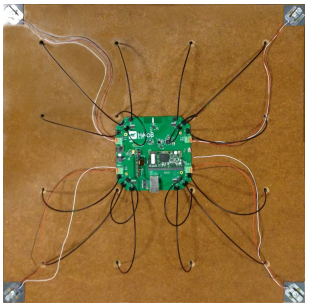
Concerning object tracking on sensing floors, inspiration can be sought in the field of computer vision, where techniques such as Bayesian Filtering [53], Joint Particle Filtering [54], Probabilistic Multi-Hypothesis Tracking [55], and Joint Probabilistic Data Association Filtering [56] have been applied for tracking multiple targets. Challa *et al.* provided an overview of these techniques in *Fundamentals of object tracking* [57]. Suutala *et al.* [58] used Gaussian Process Joint Particle Filtering to track humans on a tiled floor equipped with binary switch sensors. However, their algorithm did not use weight information to improve object tracking, as this information was not provided by their hardware. In the case of pressure-sensing floors, we can also exploit the weight information to evaluate the generated tracking hypotheses.

In this paper we present an algorithm that detects, tracks and recognizes objects by using only the information about their size and weight. It offers a solution to the problem of interpretation of spread loads, when objects span several tiles on a modular floor. In comparison to the aforementioned tracking techniques, which exploit only binary data about the presence or absence of objects, our tracking algorithm also exploits the weight data provided by load-sensing floors, as detailed in Section IV-B. As it tracks and recognizes objects individually or in groups, it is more fault tolerant as opposed to algorithms that extract gait features, which require fine segmentation and tracking of targets. This technique can boost recognition when used complementarily with algorithms that extract features from the human gait, but can also serve as a gracefully degraded recognition mode whenever these fail.

III. Load sensing equipment

We have implemented our object recognition algorithm on the *SmartTiles platform* [6], which is installed in our ambient intelligence prototype apartment (see Fig. 4). This

load-sensing floor is composed of square tiles, each equipped with 4 pressure sensors (strain gauge load cells), two ARM processors (Cortex m3 and a8), and a wired connection to the four neighbouring cells (see Fig. 1). The processing units were manufactured by Hikob[1]. The tiles' architecture is presented in Fig. 2. As shown in the diagram, both centralized and decentralized applications can be supported, thanks to the computing units embedded in the tiles. The tiles form a network of load-sensors, as represented in Fig. 5.



(a) Underside of a load-sensing tile. The load sensors are in the corners of the tile.

(b) The SparkFun SEN-10245 load sensor used. Source: www.sparkfun.com/products/10245

Figure 1: An image of a tile and a load-sensor.

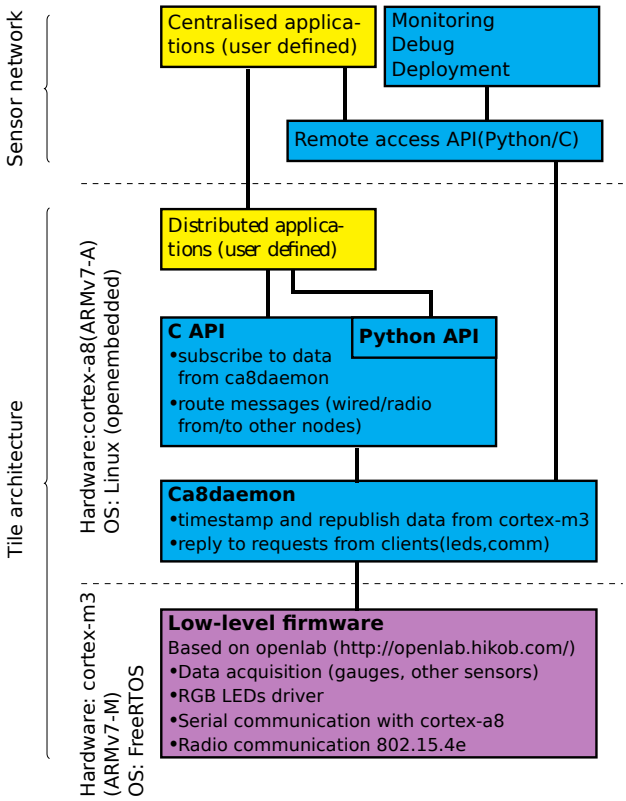


Figure 2: Tile architecture. Low-level firmware is the violet block, blue blocks form the middleware, while high-level software blocks are in yellow.

[1]http://www.hikob.com/

This prototype was originally designed as a medium of interaction for robots with distributed control, in an ant-like fashion. The computing unit available on each tile can register a virtual pheromone trace, that can then be transmitted to other robots, using either wired or wireless communication.

In a different perspective, the sensing-floor acts as a sensor for an ambient intelligence. It can measure pressure forces with the load sensors installed under the tiles, measuring static weights with a precision of up to $\pm$ 2 kg. The floor can also detect disturbances in the surrounding magnetic field caused by the presence of robots, using magnetometers embedded on the processing units of the tiles.

Each tile also has an embedded accelerometer, that allows it to detect shocks that can be caused by objects or humans falling on the ground. Floor devices of similar functionality, such as the SensFloor [50] that can detect people lying on the ground are already employed in nursing homes in France. Each tile has 16 light-emitting diodes which provide visual feedback.

The floor can localize the exerted punctual pressures, with an accuracy beyond the size of a tile. Punctual pressures can be located through a calculation of the center of pressures measured by the load sensors. The precision is influenced by the signal to noise ratio, as visible in Fig. 3.

Several functionalities have already been implemented on this prototype floor, including weight measurement, fall detection, and footstep tracking. The floor's ability to perform high resolution pressure sensing by shifting the objects on the sensing tiles has been demonstrated in [59].

This type of tiled sensing floor also has its inconvenients:

- it is incapable of distinguishing between objects of equal weight;
- its resolution depends on the size of the tiles, which are usually quite large (30 cm x 30 cm or bigger);
- its sensitivity depends on the sensitivity of its sensors;
- perception of forces is limited to the floor plane;

This floor is also capable of detecting and measuring footsteps with high accuracy, extracting them using the variations in the translation speed of the center of pressure, as described in [60]. We also implemented heuristic real-time multi-user localisation (without user identification) in an indoor setting using this prototype floor. This paper focuses on the object detection, tracking and recognition capability of such a load-sensing tiled floor.

IV. Methodology: Load Data Processing Flow

Parallels can be drawn between data processing in the context of computer vision and that of load-sensing floors. The field of view of a camera is analagous to the surface covered by a sensing floor. The light-intensity bitmap image generated by a camera is analagous to the load image generated by a load-sensing floor. This hints that traditional image processing techniques can be employed to solve similar problems in the context of load-sensing floors.

The traditional data processing flow in computer vision usually consists of the following steps: background subtraction, blob detection, blob tracking, and blob recognition. The data

flow processing that we propose for load-sensing floors is similar, and has the following structure: background subtraction, blob detection using *connected-component labeling*, and a feedback loop perfoming blob tracking and localisation of objects (see Fig. 6). The algorithm receives as input:

- the force values registered by the sensors composing the floor when there is nothing on it (i.e. the zero values used for background subtraction);
- the values of forces recorded at time t, together with the coordinates of the load sensors that sensed them;
- a list containing the models of objects known to the floor.

The object models have the following structure: object name, mass (in kilograms), and length (in meters).

A. Object detection

Objects are detected on the floor by background subtraction and subsequent *connected-component labeling*. The background subtraction allows to process the data from sensors that perceived force values above zero, filtering out all other sensors. Then, *connected-component labeling* [61] links together all sensors that are potentially supporting the same object, thereby forming blobs. It uses the length of the largest known object as a proximity threshold: if two sensors detected pressures over the noise threshold, and if the distance between the sensors is smaller than the size of the biggest known object, these are linked together, forming a connected component.

The size of the largest known object is calculated from the list of known object models. After this phase, any object present on the floor is guaranteed to be contained by one blob at most. On the other hand, a blob may contain one or several objects.

For simplicity reasons, we will consider that there is no occlusion in our system, which occurs when a tile malfunctions and stops sending load data.

In our implementation, the set of sensors is represented as a graph (see Fig. 6). Blobs are formed by the sensors left after background subtraction, which are linked using *connected-component labeling*. The blobs correspond to the connected components present in this graph. Figure 6 shows the set of load sensors embedded into the floor, where each sensor is represented as a dot. The blobs detected by the floor were then overlayed onto this image.

B. Object tracking

After the detection of blobs on the floor, we can try to infer the objects located in these blobs by using their weight. However, the load force detected by the sensors oscillates during activities such as walking or squatting and standing up (see Fig. 7 for an example). Thus, the value of this force cannot be directly converted into an estimation of an object's mass. Nevertheless, the value of this force oscillates around the weight of the object or person, as mentioned in [1]. Therefore, it is possible to approximate the total weight of objects inside a blob, by calculating the blob's average weight over a sliding window of time. This requires blob tracking.

An adequate solution to this problem is to use a tracking technique that takes into consideration the different ways in which blobs can evolve. A blob can appear in the scene, disappear, remain constant, merge with other blobs, split into several blobs, or it can exchange contents with another blob. We propose a method that explores the entire search space of joint blob evolution hypotheses (except for remote content exchange between blobs, rarely encountered in practice), and sorts these hypotheses according to a given criterion. Intuitively, the optimal solution should minimize the total distance travelled by the blobs inside the scene between two instants of time, as well as minimize the weight difference between the correlated blobs in two neighboring time frames. We define penalties for each type of blob evolution, which are used for ranking the tracking hypotheses (see Table II).

An *appear* evolution penalizes the weight of the appeared blob, as well as the distance between the new blob and the entry/exit location of the environment. Symmetrically, a *disappear* evolution penalizes the weight of the disappeared blob, and the distance to the exit point. A *split* evolution penalizes the difference between the weight of the parent blob

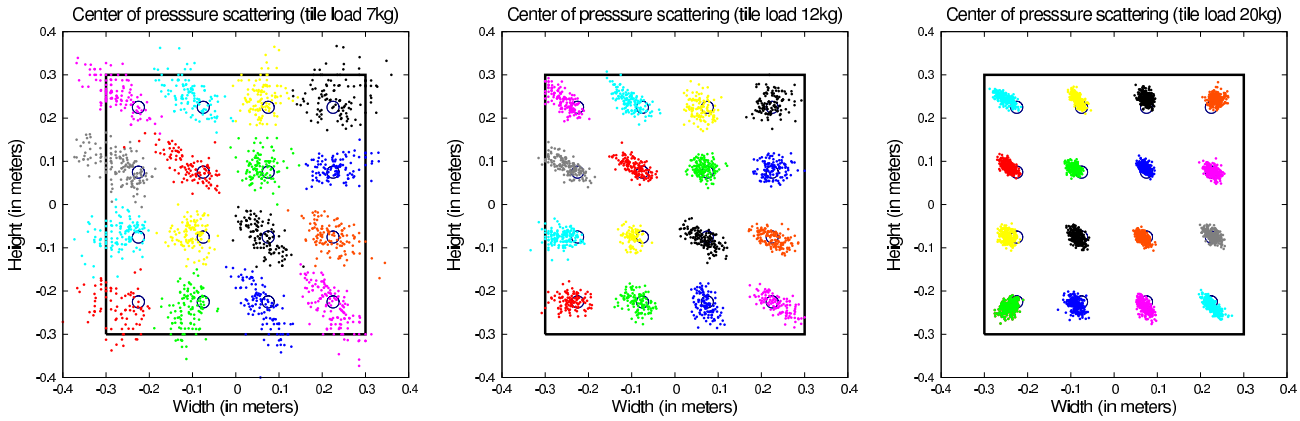


Figure 3: The scattering of the calculated center of pressure, caused by the sensor noise. The thick black square represents the load-sensing tile. Scattering is shown for 3 different loads (7kg, 12kg and 20kg) at 16 different locations of the exerted punctual pressure, marked by black circles. The higher is the ratio of signal to noise, the less scattering is observed. The indicated load does not include the weight of the tile itself, which is 10.7 kg.

and the total weight of the child blobs. A *merge* evolution penalizes the differences between the total weight of the parent blobs, and the weight of the (unified) child blob. In terms of distance, both *split* and *merge* penalize the euclidean distance between parent and child blobs. However, this distance penalty is considered nil for the parent and child blobs that overlap and occupy the same surface tiles (e.g. all the split child blobs that are contained within the surface of the parent blob; all the merged parent blobs that are contained within the surface of the unified child blob).

The final score of a hypothesis is obtained by first dividing the distance penalty and the weight penalty by their corresponding average noise values, squaring the results, and then summing them up to obtain the mixed final score. The joint blob evolution hypothesis with the lowest penalty is considered to be the most probable one.

C. Object recognition

Object recognition on load sensing surfaces can be performed by using the weight of objects, or by using their surface of contact with the floor [59]. Recognition by weight is trivial when tracking single objects or when performed on high resolution pressure sensors, that can easily segment objects on the floor. However, the problem is less trivial when tracking multiple entities, each with multiple points of support, and which interact on noisy, low-resolution sensors.

Background subtraction, connected-component labeling, and blob tracking, described in the previous sections IV-A and IV-B, reduce the problem to recognizing the contents of blobs of known weight, which support the weight of one or more objects in their entirety. This allows us to model the recognition task as an instance of a Multiple Knapsack Problem, interpreting the weights of detected blobs as knapsacks' volumes, that have to be optimally filled with known objects' weights. This is based on the hypothesis that the average weight of a blob is optimally matched by the weights of the objects it contains (see Fig. 8).

This can be formalised as follows:

- $\mathcal{O}$ is the set of known objects;
- $\mathcal{P}(\mathcal{O})$ is the set of all combinations of known objects (it is the power set of $\mathcal{O}$);
- $C = \{blob_1, \ldots, blob_n\}$ is the set of all blobs observed at a given time t. Each blob is defined by its location and weight.

All the possible assignments of objects to blobs are considered and ranked in ascending order, by using the total mismatch in weight between the blobs and the objects assigned to them (see Fig. 9). For each hypothetical assignment of objects to blobs, these mismatches are squared and then summed, so as to give preference to small mismatches, rather than large ones. The weight mismatch (or the penalty) of an assignment of objects to blobs is given by:

$$\sum_{id=1}^{\text{total blobs}} \Big(\text{weight}\big(\text{blob}_{id}\big) - \text{weight}\big(\text{contents}\,(\text{blob}_{id})\,\big)\Big)^2 \quad (1)$$

The size of the search space, that is the number of possible assignments to analyse, is given by:

$$(\text{number of blobs + 1})^{(\text{number of known objects})} \quad (2)$$

As highlighted by eq. 2, there is a risk of a combinatorial explosion when performing this exhaustive search. This can be dealt with using traditional techniques like *branch and bound*, and *dynamic progamming*.

Given the contents of blobs in the previous timestep, and given a hypothesis on how the blobs have evolved inside the scene from the previous to the current timestep, we can infer the contents of blobs at the current timestep. However, this requires bootstrapping the knowledge about the contents of blobs at some initial time t_{start}.

As the blobs inside the scene evolve, the candidate recognition solutions will cumulate penalties over time. The candidate solution with the minimal total penalty over time is considered to be the best guess (see Fig. 10).

The result of the recognition algorithm is a list of assignments of objects to blobs, ordered according to their cumulated penalties. Intuitively, the assignment having the minimal penalty is considered to be the most probable one.

For probabilistic reasoning algorithms, a measure describing the probability for an assignment of not being the correct solution can be introduced: this is the penalty of the assignment, normalized using the sum of all assignments' penalties (see eq. 3).

$$P(\neg Assignment_k) = \frac{\text{Penalty}(\text{Assignment}_k)}{\sum_{id=1}^{\text{total assignments}} \text{Penalty}(\text{Assignment}_{id})} \quad (3)$$

V. Experiments

We evaluate our approach by running experiments with humans performing daily life activities: doing the morning routine (waking up in the bed, using the toilet, having breakfast), and receiving a visitor (opening the door, leading the

	Appear / Disappear	Merge	Split
Distance penalty	$\left(\frac{distanceTo(entrance/exit)}{avg\ COP\ scattering\ noise}\right)^2$	$\sum^{\text{non-overlapping parents}} \left(\frac{distanceTo(childBlob)}{average\ COP\ scattering\ noise}\right)^2$	$\sum^{\text{non-overlapping children}} \left(\frac{distanceTo(parentBlob)}{average\ COP\ scattering\ noise}\right)^2$
Weight penalty	$\left[\frac{weight(blob)}{avg\ pressure\ noise}\right]^2$	$\left[\frac{\left(\sum^{\text{parents}} weight(blob)\right) - weight(childBlob)}{average\ pressure\ noise}\right]^2$	$\left[\frac{weight(parentBlob) - \left(\sum^{\text{children}} weight(blob)\right)}{average\ pressure\ noise}\right]^2$

Table II: Calculation of penalties for each type of blob evolution

Figure 4: 3D model of the intelligent apartment prototype, with the load-sensing floor.

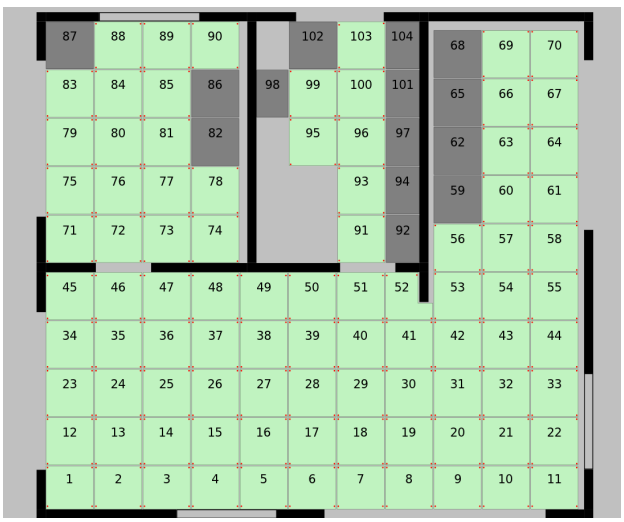


Figure 5: 2D image of the tiles composing the floor, with the sensors highlighted in red. Gray tiles are not equipped with sensors.

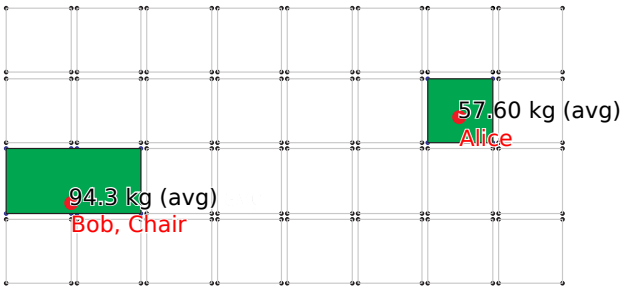


Figure 6: Object recognition sample. The floor load sensors are represented as little black dots. The detected blobs are colored in green. The numbers in black show the average blob weight, calculated over a time window. The red dots show the position of blobs' centers of mass. The text in red shows the recognition guess.

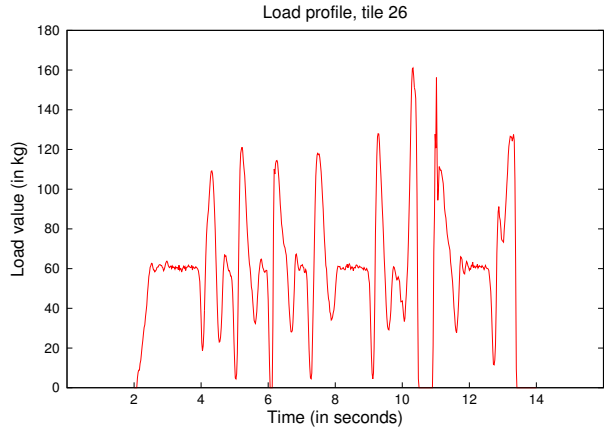


Figure 7: The load profile of a person squatting and jumping on a load-sensing tile. Notice that the load oscillation is centered around the mass of the person, which is 60 kg.

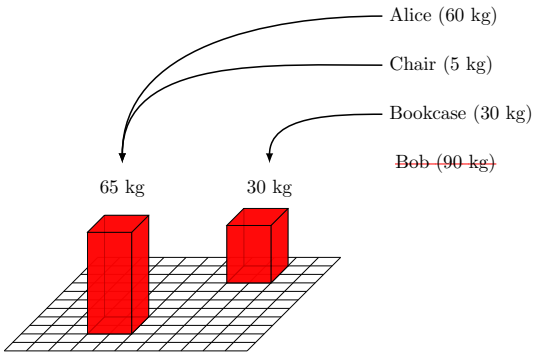


Figure 8: Object recognition modeled as a Multiple Knapsack Problem.

Assignment$_1$		**Assignment$_i$**		**Assignment$_{(\mathbf{blobs+1})^{\mathbf{objects}}}$**
Object$_1$ $\rightarrow \emptyset$		Object$_1$ $\rightarrow$ Blob$_2$		Object$_1$ $\rightarrow$ Blob$_k$
Object$_2$ $\rightarrow \emptyset$	...	Object$_2$ $\rightarrow \emptyset$	...	Object$_2$ $\rightarrow$ Blob$_k$
...		...		...
Object$_n$ $\rightarrow \emptyset$		Object$_n$ $\rightarrow$ Blob$_k$		Object$_n$ $\rightarrow$ Blob$_k$

Figure 9: All the possible assignments of known objects to blobs are evaluated and ordered according to how well the blobs are matched in terms of weight by their contents. The assignment having the minimal weight mismatch is considered as most probable.

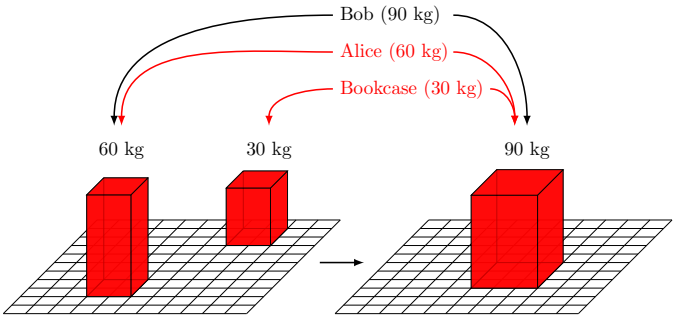


Figure 10: The optimal assignment of objects to blobs cumulates the minimal penalty over time.

(a) The bedroom and living room.

(b) The living room, the bathroom and the kitchen.

Figure 11: The prototype apartment with the tiled sensing floor.

visitor into the living room, having a chat while seated, eating a cake, leading the visitor to the exit). All scenarii involve multi-object detection, tracking and localisation. The experiments took place in our prototype apartment (Fig. 11).

During the whole duration of these activities, the sensing floor had to localize the persons and objects inside the scene. The center of pressure (COP) of a blob was considered as the location of all the objects contained by this blob. An approximation of the ground truth was provided by a Qualisys [2] motion tracking system (tracking error below 1 mm), which recorded the vertical projection of markers placed on objects' approximate centers of mass. Each human had a reflector placed on his waist, so that its vertical projection onto the ground plane would approximately correspond to his COP (fig. 13a and 14a). The experimental results are presented as measurements of the localisation precision. These measurements were made only when both localisation data were available: the approximate ground truth given by the motion tracking system, and the localisation provided by the floor. This explains the interruptions in the curves showing the localisation precision.

A. Baseline precision

To gain an understanding of the baseline precision of the floor sensor, we performed an experiment with a non-holonomic 4-wheeled robot (robuLAB-10 by Robosoft[3]) rolling on the floor of the apartment. The idea was to track the fluid movement of an autonomous robot, as compared to the saccadic movements of the COP which are characteristic for the human gait. As we had no ground truth for the localisation of robot's center of pressure, we used an approximation using the data from the motion tracking system. Considering that the robot is rigid, we could estimate the position of its COP using the least squares method, by calculating the point which minimized the quadratic distance error between itself and the center of pressure calculated by the sensing floor.

The robot was localised by the sensing floor with an average precision of 8 cm for free movement, and a standard deviation of 5 cm, as shown in Fig. 12.

B. Morning routine scenario

The *morning routine* scenario involved a person performing a set of daily life activities, such as: sleeping in bed, using the toilet, having breakfast, and leaving the house (see Fig. 13). The challenges of this scenario included tracking multiple interacting entities on a low resolution sensor, as well as the presence of ambiguity between objects of similar weight.

As we had no system to provide us with the ground truth for the localisation of a person's COP, the measured localisation error obtained using the COP approximation given by the motion tracking system is expected to be higher than the real localisation error. In contrast to rigid robots, humans are flexible. This did not allow us to calculate an approximation of the COP using the least squares method, as we had done in the baseline case with a rigid robot.

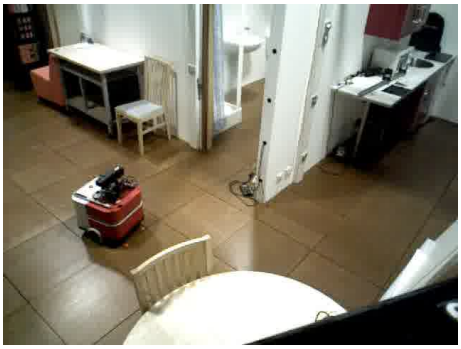
The localisation errors for the human (average error 13 cm) and the bed (average error 19 cm) are shown in Fig. 13b. When the person interacts with the bed, the two are segmented together in a single blob, with the COP closer to the heavier human, which explains his better localisation. The localisation error is the biggest at the beginning and end of each interaction, when the two entities begin approaching each other, forming an elongated blob. The localisation error is at its lowest during the close interactions between objects, when the blob regrouping the interacting objects is compact. We observe 15 cm of localisation error for the bed when it is at rest, and a higher error during interactions, which depends on the proximity with the interacting entity and its relative weight.

Fig. 13c shows the localisation errors for lightweight objects, such as the chair (5.5 kg) and the dish with the breakfast (4.9 kg). A heavy plate was chosen to overcome the noise threshold of the floor sensor. We observe the same effects as previously described: the localisation error increases in the proximity of humans, due to their segmentation in a common blob, with the COP closer to the human.

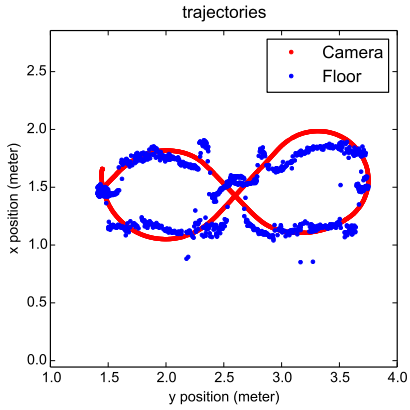
C. Receiving a visitor scenario

The *receiving a visitor* scenario involved a person hosting someone in his house. The guest would be greeted at the door by the host, enter the living room of the apartment, take a seat, wait for the host to bring something to eat, have a chat with the host, and then leave the house. The challenge was to track and locate multiple interacting persons with a low resultion sensor.

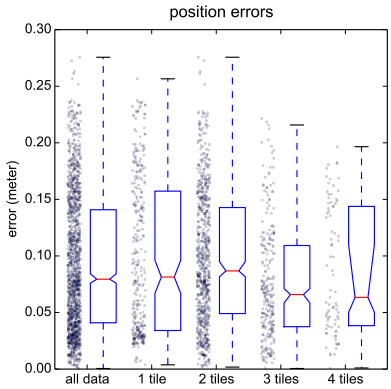
[2]http://www.qualisys.com/
[3]http://www.robosoft.com/



(a) A robuLAB-10 robot navigating on the sensing floor.



(b) The robot trajectory (red), and the localisation given by the floor (blue). The average localisation error is 8 cm, with a standard deviation of 5 cm.



(c) Tukey box plot presenting an analysis of the floor's localisation error, depending on the number of tiles supporting the robot at the time of localisation.

Figure 12: The *robotic navigation* scenario

The localisation results are shown in Fig. 14b. The average localisation error for interacting persons is around 20 cm. The drop in the localisation precision occurs when the two persons walk or stand nearby, occupying a contiguous space in terms of tiles, which prevents them from being segmented separately. Again, the measured localisation error for humans is expected to be higher than the real localisation error, as we could not approximate the position of the human's COP with the least squares method, as we did it with a rigid robot in section V-A.

D. Discussion

The presented algorithm works independently of the floor resolution (i.e. density of sensors per m^2, size of the floor tiles). However, the bigger the tiles are (the lesser the floor-image resolution is), the coarser the results of the object detection algorithm will be. Also, coarser object detection results introduce more ambiguity in object recognition and localisation. Therefore, it would be interesting to have a prototype with a higher sensor density (smaller tiles in our case), as well as less noisy sensors.

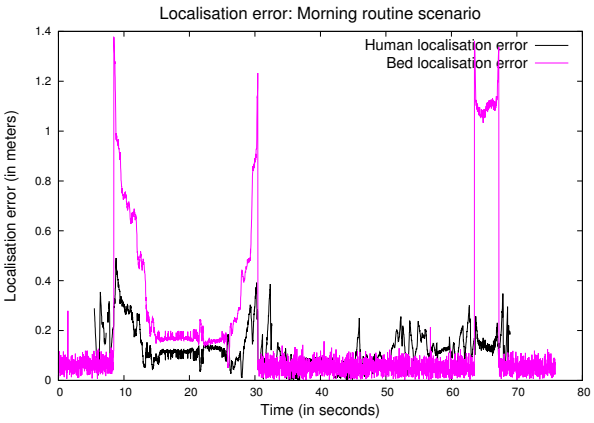
The use of these tiles dictates their smallest practical size: for footstep tracking applications, tiles having the size of a foot are sufficient. For more fine-grained details, as required by biometrical applications, other types of sensing floors may be more adequate (e.g. pressure mats), if judged by price per unit of sensing surface, or by their fabrication complexity. It would also be interesting to have sensors that capture the xyz components of the ground force. This would allow the reconstruction of the human body posture, given a model of the human body and of its constraints.

VI. Conclusion and Perspectives

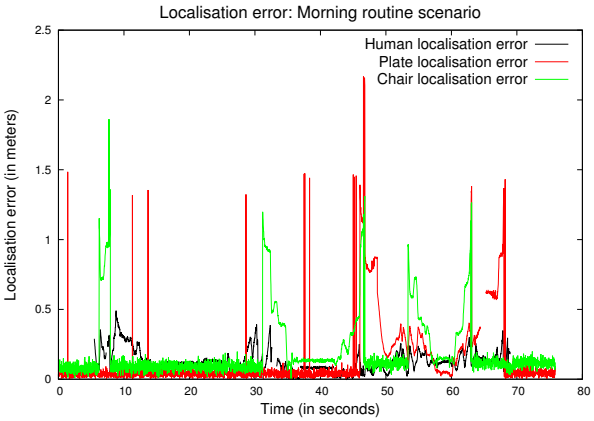
This paper presents a technique for detecting, tracking and recognising objects on load-sensing floors, using objects' weight as discriminative feature. The proposed object segmentation algorithm is a variation of *connected-component labeling*, inspired by the computer vision community, with the additional property of having entire objects segmented into blobs. This allows the interpretation of spread loads, when objects span several tiles on a modular floor. The proposed tracking algorithm considers the different ways in which blobs can interact, identifying the most probable hypotheses for the way the blobs have evolved between two timesteps. This allows to infer the objects contained in the segmented blobs, given their contents at the previous timestep, and given a hypothesis on the evolution of blobs. The resulting possible assignments of objects to blobs are ranked by the mismatch between the weight of blobs and of objects assigned to them. This is reminiscent of the *multiple knapsack problem*, with blobs acting as containers that have to be optimally filled with known objects, identifying the optimal solution using *Least Squares*. The whole localisation algorithm was evaluated in experiments with humans performing daily life activities: executing the morning routine, and receiving a visitor. Challenges included the segmentation, tracking and recognition of multiple interacting entities using a low resolution sensor, as well as disambiguation between combinations of objects of similar weight. The average error for human localisation was approximately 20 cm. The result of this algorithm can be modelled as a probability distribution over all possible assignments of objects to the blobs detected on the floor. This allows for easy integration of this algorithm into a multi-modal object recognition architecture. This technique can boost recognition when used complementarily with algorithms that extract features from gait, but can also serve as a gracefully degraded recognition mode whenever these fail.

Future work will include fine-grained tracking, obtained by assigning each detected object to a separate layer. This should allow to continuously update the set of objects composing the background, and would consequently improve segmentation. We are also working on labeling the interactions between humans and objects, which can be roughly observed using this technique. We also plan to use this data to generate logs detailing the activities performed by a person during the day:

(a) An image from the *Morning routine* scenario.



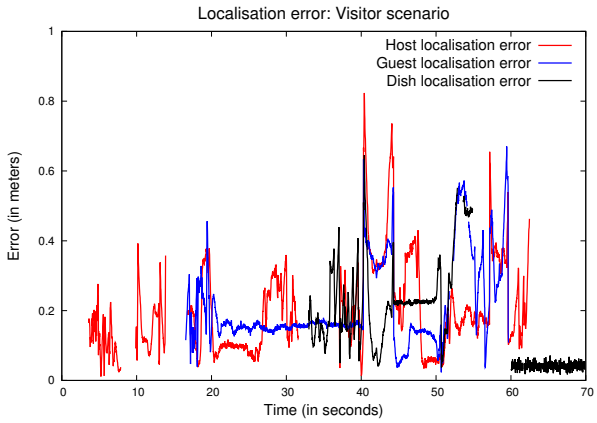
(b) Localisation error for the *Morning routine* scenario. During each interaction between the person and the bed, the center of pressure is located between the interacting entities, closer to the heaviest one (the human, in this case). The spikes between 10-30s, and between 62-68s are caused by the human approaching and leaving the bed during the interactions.



(c) Localisation error for the lightweight objects in the *Morning routine* scenario. Occasional, short-time errors in the correct assignment of objects to blobs generate the thin spikes in the localisation error. These are due to ambiguities between objects of similar weight. The spikes in the chair localisation error are due to the human proximity, having as effect the segmentation of the two in a single blob.

Figure 13: The *Morning routine* scenario

(a) An image from the scenario *Receiving a visitor*.



(b) Localisation error for the scenario with a person hosting a visitor in his house. The drop in the localisation precision occurs when the two persons walk or stand nearby, occupying a contiguous space in terms of tiles, which prevents them from being segmented separately. Average human localisation error: 20 cm.

Figure 14: The *Visitor* scenario

how many times a person got out of bed, how many steps did he make, how many persons are there in the room, etc. These activity plots are useful in hospitals and retirement homes, as they allow to trace the overall health state of a patient.

ACKNOWLEDGMENT

We are grateful to our colleagues, Thomas Moinel, Benjamin Camus, Pauline Houlgatte, Xavier Erb who helped us by acting, recording and pre-processing the developed experimental scenarii. We thank Dr. Olivier Rochel and Roger Pissard-Gibollet for the technical support in the design of the smart floor, and Dr. David Daney, Dr. Maxime Rio and Dr. Francis Colas for their scientific support. We also thank the anonymous reviewers, who provided helpful comments to this article.

This work has been mainly funded by Inria (IPL PAL) and Region Lorraine, and partly by Investissement d'Avenir reseach & industry project LAR, and the European CoDyCo project (FP7-ICT- 2011-9, No. 600716).

REFERENCES

[1] M. Addlesee, A. Jones, F. Livesey, and F. Samaria, "The ORL active floor," *Personal Communications, IEEE*, vol. 4, no. 5, pp. 35–41, oct 1997.

[2] S. Pirttikangas, J. Suutala, J. Riekki, and J. Röning, "Footstep identification from pressure signals using hidden markov models," in *Proc. Finnish Signal Processing Symposium (FINSIG'03)*, 2003, pp. 124–128.

[3] A. Schmidt, M. Strohbach, K. v. Laerhoven, A. Friday, and H.-W. Gellersen, "Context acquisition based on load sensing," in *Proceedings of the 4th international conference on Ubiquitous Computing*, ser. UbiComp '02. London, UK: Springer-Verlag, 2002, pp. 333–350. [Online]. Available: http://dl.acm.org/citation.cfm?id=647988.741476

[4] R. J. Orr and G. D. Abowd, "The smart floor: a mechanism for natural user identification and tracking," in *CHI '00 Extended Abstracts on Human Factors in Computing Systems*, ser. CHI EA '00. New York, NY, USA: ACM, 2000, pp. 275–276. [Online]. Available: http://doi.acm.org/10.1145/633292.633453

[5] S. Martello and P. Toth, *Knapsack problems*. Wiley New York, 1990.

[6] N. Pepin, O. Simonin, and F. Charpillet, "Intelligent Tiles: Putting Situated Multi-Agents Models in Real World," in *International Conference on Agents and Artificial Intelligence - ICAART'09*, ACM, AAAI, Springer, Ed., Porto, Portugal, 2009, pp. 513–519.

[7] S. Pirttikangas, J. Suutala, J. Riekki, and J. Röning, "Learning vector quantization in footstep identification," in *Proceedings of 3rd IASTED International Conference on Artificial Intelligence and Applications (AIA 2003)*, M. Hamza, Ed., IASTED. Benalmadena, Spain: ACTA Press, September 8-10 2003, pp. 413–417.

[8] J.-S. Yun, S.-H. Lee, W.-T. Woo, and J.-H. Ryu, "The user identification system using walking pattern over the ubifloor," in *Proceedings of International Conference on Control, Automation, and Systems*, vol. 1046, 2003, p. 1050.

[9] J.-W. Jung, Z. Bien, S.-W. Lee, and T. Sato, "Dynamic-footprint based person identification using mat-type pressure sensor," in *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, vol. 3, Sept 2003, pp. 2937–2940 Vol.3.

[10] J.-W. Jung, T. Sato, and Z. Bien, "Dynamic footprint-based person recognition method using a hidden markov model and a neural network," *International Journal of Intelligent Systems*, vol. 19, no. 11, pp. 1127–1141, 2004. [Online]. Available: http://dx.doi.org/10.1002/int.20040

[11] J. Suutala and J. Röning, "Towards the adaptive identification of walkers: Automated feature selection of footsteps using distinction-sensitive lvq," in *Int. Workshop on Processing Sensory Information for Proactive Systems (PSIPS 2004)*, 2004, pp. 14–15.

[12] J. Suutala and J. Roning, "Combining classifiers with different footstep feature sets and multiple samples for person identification," in *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on*, vol. 5, March 2005, pp. v/357–v/360 Vol. 5.

[13] L. Middleton, A. Buss, A. Bazin, and M. S. Nixon, "A floor sensor system for gait recognition," in *Proceedings of the Fourth IEEE Workshop on Automatic Identification Advanced Technologies*, ser. AUTOID '05. Washington, DC, USA: IEEE Computer Society, 2005, pp. 171–176.

[14] J. Yun, W. Woo, and J. Ryu, "User identification using user's walking pattern over the UbiFloorII," in *Computational Intelligence and Security*, ser. Lecture Notes in Computer Science, Y. Hao, J. Liu, Y. Wang, Y.-m. Cheung, H. Yin, L. Jiao, J. Ma, and Y.-C. Jiao, Eds. Springer Berlin Heidelberg, 2005, vol. 3801, pp. 949–956.

[15] J. Yun, G. D. Abowd, J. Ryu, and W. Woo, "User identification with user's stepping pattern over the UbiFloorII," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 22, no. 03, pp. 497–514, 2008.

[16] J. Suutala and J. Röning, "Methods for person identification on a pressure-sensitive floor: Experiments with multiple classifiers and reject option," *Information Fusion*, vol. 9, no. 1, pp. 21 – 40, 2008, special Issue on Applications of Ensemble Methods.

[17] J. Suutala, K. Fujinami, and J. Röning, "Gaussian process person identifier based on simple floor sensors," in *Smart Sensing and Context*, ser. Lecture Notes in Computer Science, D. Roggen, C. Lombriser, G. Tröster, G. Kortuem, and P. Havinga, Eds. Springer Berlin Heidelberg, 2008, vol. 5279, pp. 55–68.

[18] G. Qian, J. Zhang, and A. Kidané, "People identification using gait via floor pressure sensing and analysis," in *Smart Sensing and Context*, ser. Lecture Notes in Computer Science, D. Roggen, C. Lombriser, G. Tröster, G. Kortuem, and P. Havinga, Eds. Springer Berlin Heidelberg, 2008, vol. 5279, pp. 83–98.

[19] R. Vera-Rodriguez, J. Mason, and N. Evans, "Assessment of a footstep biometric verification system," in *Handbook of Remote Biometrics*, ser. Advances in Pattern Recognition, M. Tistarelli, S. Li, and R. Chellappa, Eds. Springer London, 2009, pp. 313–327.

[20] G. Qian, J. Zhang, and A. Kidané, "People identification using floor pressure sensing and analysis," *Sensors Journal, IEEE*, vol. 10, no. 9, pp. 1447–1460, Sept 2010.

[21] R. Vera-Rodriguez, J. Mason, J. Fierrez, and J. Ortega-Garcia, "Analysis of time domain information for footstep recognition," in *Advances in Visual Computing*, ser. Lecture Notes in Computer Science, G. Bebis, R. Boyle, B. Parvin, D. Koracin, R. Chung, R. Hammoud, M. Hussain, T. Kar-Han, R. Crawfis, D. Thalmann, D. Kao, and L. Avila, Eds. Springer Berlin Heidelberg, 2010, vol. 6453, pp. 489–498.

[22] J. Yun, "User identification using gait patterns on UbiFloorII," *Sensors*, vol. 11, no. 3, pp. 2611–2639, 2011.

[23] R. Vera-Rodriguez, J. Mason, J. Fierrez, and J. Ortega-Garcia, "Comparative analysis and fusion of spatiotemporal information for footstep recognition," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 35, no. 4, pp. 823–834, April 2013.

[24] J. Paradiso, C. Abler, K.-y. Hsiao, and M. Reynolds, "The magic carpet: physical sensing for immersive environments," in *CHI '97 Extended Abstracts on Human Factors in Computing Systems*, ser. CHI EA '97. New York, NY, USA: ACM, 1997, pp. 277–278.

[25] S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, and E. Jansen, "The gator tech smart house: a programmable pervasive space," *Computer*, vol. 38, no. 3, pp. 50 – 60, March 2005.

[26] C. D. Kidd, R. Orr, G. D. Abowd, C. G. Atkeson, I. A. Essa, B. MacIntyre, E. D. Mynatt, T. Starner, and W. Newstetter, "The aware home: A living laboratory for ubiquitous computing research," in *Proceedings of the Second International Workshop on Cooperative Buildings, Integrating Information, Organization, and Architecture*, ser. CoBuild '99. London, UK: Springer-Verlag, 1999, pp. 191–198.

[27] T. Mori and T. Sato, "Robotic room: Its concept and realization," *Robotics and Autonomous Systems*, vol. 28, no. 2-3, pp. 141–148, 1999.

[28] T. Sato, T. Harada, and T. Mori, "Environment-type robot system "RoboticRoom" featured by behavior media, behavior contents, and behavior adaptation," *Mechatronics, IEEE/ASME Transactions on*, vol. 9, no. 3, pp. 529 –534, sept. 2004.

[29] T. Mori, Y. Suemasu, H. Noguchi, and T. Sato, "Multiple people tracking by integrating distributed floor pressure sensors and RFID system," in *Systems, Man and Cybernetics, 2004 IEEE International Conference on*, vol. 6, Oct 2004, pp. 5271–5278 vol.6.

[30] I. Al-Naimi, C. B. Wong, P. Moore, and X. Chen, "Advanced approach for indoor identification and tracking using smart floor and pyroelectric infrared sensors," in *Information and Communication Systems (ICICS), 2014 5th International Conference on*, April 2014, pp. 1–6.

[31] M. Sousa, A. Techmer, A. Steinhage, C. Lauterbach, and P. Lukowicz, "Human tracking and identification using a sensitive floor and wearable accelerometers," in *Pervasive Computing and Communications (PerCom), 2013 IEEE International Conference on*, March 2013, pp. 166–171.

[32] T. Ikeda, H. Ishiguro, and T. Nishimura, "People tracking by fusing different kinds of sensors, floor sensors and acceleration sensors," in *Multisensor Fusion and Integration for Intelligent Systems, 2006 IEEE International Conference on*, Sept 2006, pp. 530–535.

[33] P. Srinivasan, D. Birchfield, G. Qian, and A. Kidané, "A pressure sensing floor for interactive media applications," in *In Proceedings of ACM SIGCHI International Conference on Advances in Computer Entertainment Technology (ACE), 2005. (Ref*, 2005, p. 26.

[34] C.-R. Yu, C.-L. Wu, C.-H. Lu, and L.-C. Fu, "Human localization via multi-cameras and floor sensors in smart home," in *Systems, Man and Cybernetics, 2006. SMC '06. IEEE International Conference on*, vol. 5, Oct 2006, pp. 3822–3827.

[35] GAITRite, "Gaitrite portable walkway system." [Online]. Available: www.gaitrite.com

[36] Kistler force plates. [Online]. Available: http://www.kistler.com/us/en/index

[37] B. Heller, T. Senior, and J. Wheat, "The smartfloor: A large area force-measuring floor for investigating dynamic balance and motivating exercise," *Procedia Engineering*, vol. 72, no. 0, pp. 226 – 231, 2014, the Engineering of Sport 10.

[38] R. Rajalingham, Y. Visell, and J. Cooperstock, "Probabilistic tracking of pedestrian movements via in-floor force sensing," in *Computer and Robot Vision (CRV), 2010 Canadian Conference on*, May 2010, pp. 143–150.

[39] S. Rangarajan, A. Kidané, G. Qian, S. Rajko, and D. Birchfield, "The design of a pressure sensing floor for movement-based human computer

interaction," in *Smart Sensing and Context*, ser. Lecture Notes in Computer Science, G. Kortuem, J. Finney, R. Lea, and V. Sundramoorthy, Eds. Springer Berlin Heidelberg, 2007, vol. 4793, pp. 46–61.

[40] H. Morishita, R. Fukui, and T. Sato, "High resolution pressure sensor distributed floor for future human-robot symbiosis environments," in *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, vol. 2, 2002, pp. 1246 – 1251 vol.2.

[41] T. Murakita, T. Ikeda, and H. Ishiguro, "Human tracking using floor sensors based on the markov chain monte carlo method," in *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, vol. 4, aug. 2004, pp. 917 – 920 Vol.4.

[42] D. Savio and T. Ludwig, "Smart carpet: A footstep tracking interface," in *Proceedings of the 21st International Conference on Advanced Information Networking and Applications Workshops - Volume 02*, ser. AINAW '07. Washington, DC, USA: IEEE Computer Society, 2007, pp. 754–760.

[43] M. Valtonen, J. Maentausta, and J. Vanhala, "Tiletrack: Capacitive human tracking using floor tiles," in *Pervasive Computing and Communications, 2009. PerCom 2009. IEEE International Conference on*, March 2009, pp. 1 –10.

[44] A. Braun, H. Heggen, and R. Wichert, "Capfloor - a flexible capacitive indoor localization system," in *Evaluating AAL Systems Through Competitive Benchmarking. Indoor Localization and Tracking*, ser. Communications in Computer and Information Science, S. Chessa and S. Knauth, Eds. Springer Berlin Heidelberg, 2012, vol. 309, pp. 26–35.

[45] M. Lombardi, A. Pieracci, P. Santinelli, R. Vezzani, and R. Cucchiara, "Sensing floors for privacy-compliant surveillance of wide areas," in *Advanced Video and Signal Based Surveillance (AVSS), 2013 10th IEEE International Conference on*, Aug 2013, pp. 105–110.

[46] Y.-L. Shen and C.-S. Shin, "Distributed sensing floor for an intelligent environment," *Sensors Journal, IEEE*, vol. 9, no. 12, pp. 1673 –1678, dec. 2009.

[47] T. Lee, Y. Kwon, and H. Kim, "Smart location tracking system using fsr (force sensing resistor)," in *International Conference on Artificial Reality and Telexistence*, 2004.

[48] Y. Visell, S. Smith, A. Law, R. Rajalingham, and J. Cooperstock, "Contact sensing and interaction techniques for a distributed, multimodal floor display," in *3D User Interfaces (3DUI), 2010 IEEE Symposium on*, March 2010, pp. 75–78.

[49] The Active Gaming Company, "Lightspace floor." [Online]. Available: http://www.the-agc.com/products/physical-therapy/lightspace-floor/

[50] C. Lauterbach, A. Steinhage, and A. Techmer, "Large-area wireless sensor system based on smart textiles," in *Systems, Signals and Devices (SSD), 2012 9th International Multi-Conference on*, March 2012, pp. 1–2.

[51] Tarkett, "FloorInMotion." [Online]. Available: http://www.floorinmotion.com/

[52] M. Contigiani, E. Frontoni, A. Mancini, and A. Gatto, "Indoor people localization and tracking using an energy harvesting smart floor," in *Mechatronic and Embedded Systems and Applications (MESA), 2014 IEEE/ASME 10th International Conference on*. IEEE, 2014, pp. 1–5.

[53] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello, "Bayesian filtering for location estimation," *IEEE pervasive computing*, no. 3, pp. 24–33, 2003.

[54] H. A. Blom and E. A. Bloem, "Joint particle filtering of multiple maneuvering targets from unassociated measurements." *J. Adv. Inf. Fusion*, vol. 1, no. 1, pp. 15–34, 2006.

[55] P. Willett, Y. Ruan, and R. Streit, "Pmht: problems and some solutions," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 38, no. 3, pp. 738–754, Jul 2002.

[56] T. E. Fortmann, Y. Bar-Shalom, and M. Scheffe, "Sonar tracking of multiple targets using joint probabilistic data association," *Oceanic Engineering, IEEE Journal of*, vol. 8, no. 3, pp. 173–184, Jul 1983.

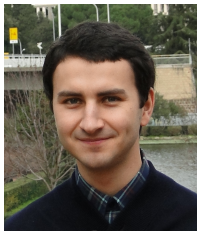
[57] S. Challa, M. R. Morelande, D. Musicki, and R. J. Evans, "Fundamentals of object tracking," 2011.

[58] J. Suutala, K. Fujinami, and J. Roning, "Persons tracking with gaussian process joint particle filtering," in *Machine Learning for Signal Processing (MLSP), 2010 IEEE International Workshop on*, Aug 2010, pp. 160–165.

[59] M. Andries, F. Charpillet, and O. Simonin, "High resolution pressure sensing using sub-pixel shifts on low resolution load-sensing tiles," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, Seattle, United States, May 2015.

[60] L. Ballaz, M. Raison, C. Detrembleur *et al.*, "Decomposition of the vertical ground reaction forces during gait on a single force plate," *Journal of musculoskeletal & neuronal interactions*, vol. 13, no. 2, pp. 236–243, 2013.

[61] M. B. Dillencourt, H. Samet, and M. Tamminen, "A general approach to connected-component labeling for arbitrary image representations," *J. ACM*, vol. 39, no. 2, pp. 253–280, apr 1992.



Mihai Andries (S'13) received his B.S. degree in computer science (2010) and M.S. degree in software and data engineering (2012) from the University of Strasbourg in Strasbourg, France. He is currently a Ph.D. candidate at the University of Lorraine, in Nancy, France.

From 2010 to 2012, he was with PSA Peugeot-Citroen in Montbeliard, France, where he was involved with modeling software architectures for the automotive industry. Since 2012, he has been a doctoral researcher at the Inria Nancy - Grand-Est research center in Nancy, France.

Mr. Andries has been a member of the French Association for Artificial Intelligence (AFIA) since 2011.

Olivier Simonin (M'12) was born in Nîmes, France, on November 12, 1973. He received the B.S, M.S. and Ph.D. degrees in computer science from Université Montpellier II, France, in 1995, 1997 and 2001 respectively.

From 2002 to 2006 he was an Associate Professor at UTBM, Université de Technologie de Belfort-Montbeliard, and with the SeT laboratory, Systems and Transport, France. From 2006 to 2013, he was an Associate Professor at Université de Lorraine (Nancy 1) and with the LORIA Laboratory as a member of the Inria project-team MaIA (Autonomous and Intelligent Machines). At present, he is full Professor at INSA de Lyon (University of Lyon) and with the CITI-Inria Lab. In 2015 he created the Inria team Chroma, Cooperative and Human-aware Robot Navigation in Dynamic Environments, co-located at Inria Grenoble - Rhône-Alpes and CITI Lab. His research is concerned with distributed and bio-inspired decision-making models for mobile robotics.

François Charpillet received his Dipl. Ing. degree from École Nationale Supérieure d'Électricité et de Mécanique (ENSEM) of the National Polytechnic Institute of Lorraine (INPL) in 1982. He received the M.S. and Ph.D. degree in computer science from Henri Poincaré University, Nancy, France, in 1982 and 1985 respectively.

After a period as an engineer at Direction des Constructions Navales (DCN) in Paris, he joined the University of Lorraine and LORIA Lab as an assistant professeur in 1987. In 1988, he got a research position at Inria Nancy - Grand-Est Research Center. He is today Director of Research at Inria. From 1998 to 2014, he has been the leader of LORIA team MAIA, which was a joint research group with Inria, CNRS and University of Lorraine. This group was interested in Artificial Intelligence focusing on autonomous agents and multi-agent systems. Since 2015, he is the scientific leader of the new Inria team Larsen, focusing on Long Term Robotics, Human-robot interaction and Active and Distributed sensing. His current research interests concern multi-robot cooperation, human-robot-environment interaction, activity recognition, active sensing and ambient Intelligence.