Detecting occupancy and social interaction via energy and environmental monitoring

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Abstract: The demand for human oriented services in indoor environment has received steady interest and it is represent a big challenge for increasing the human well-being. In this work, we present a system able to perform room occupancy detection and social interactions identification, using data coming from both energy consumption information and environmental data. We also study the application of supervised and unsupervised learning techniques to the reference scenario, in order to: i) infer context information related to socialization aspects, by recognizing in real-time social interactions; ii) identify when a room is really occupied by workers or not, for emergencies management. The system has been tested in a real workplace scenario, inside three rooms of the CNR research area in Pisa occupied by different numbers of workers, representing the main core technology for future Active and Assisted Living services.

Keywords: Occupancy Detection; Social Interactions; Wireless Sensor Network

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1 Introduction

According to EPA (http://www.epa.gov/) and UNECE (http://www.unece.org/), urban residents spend more than 90% of their time in buildings, such as homes, schools, and offices. Therefore, in recent years, the Ambient Intelligence (AmI) paradigm has arisen from the increasingly availability of ICT solutions, low-cost sensors and actuators, and wearable devices. Consequently, the knowledge of the status of the indoor environment, such as rooms, corridors, desks, have received steady interest. The reasons are twofold. On one hand, usage statistics are needed in order to assist users in their own environment for safety and comfortable issues. On the other hand, the presence of intelligent systems able to perform monitoring and detection tasks of the human well-being, can lead to prevent illnesses or pathological situations (i.e. people becoming socially isolated). Depression tends to affect people in their prime working years and may last a lifetime if untreated. More than 80 percent of people with clinical depression can be successfully treated with early recognition, intervention, and support (Kirk et al. (2003)). Furthermore, people who suffer from these diseases can be trapped in a vicious circle, losing energy and interest, preventing further positive experiences, both in domestic and working places. Finally, detecting the presence of employee in their offices is extremely useful in many other applications such as security and, in general, human-centered environmental control. We identified the awareness of room occupancies and social interactions as the main pillars for monitoring the well-being in workplaces and managing emergency situations.

In this work, we address these issues realizing a system able to detect the room occupancy status and to identify social interaction among workers in indoor environments, unobtrusively. Our system has been deployed and tested into a real indoor workplace, representing a key component of broader Ambient Assisted Living (http://www.aal-europe.eu) (AAL) systems.

To this end, we developed a Wireless Sensor Network (WSN), installed in three offices of our institute, where each node is equipped with transducers able to measure environmental parameters (e.g., humidity, noise, and movements) and the power consumption of the entire office. In particular, we chose the ZigBee technology (Palumbo et al. (2013)) since it represents a standard-based wireless technology designed to address the unique needs of low-power wireless sensor networks, and it also has a rich model for the representation of device capabilities. From an algorithmic point of view, we applied state of the art techniques in the area of supervised and unsupervised learning in order to test their adaptability to the peculiarities of the dataset, highlighting advantages and disadvantages.

The paper is organized as follows: Section 2 presents the state of the art on monitoring systems and well-being issues in workplaces, Section 3 shows the overview of the proposed system, Section 4 describes the used methodological and algorithmic approach, while Section 5 shows the experimental setup and the obtained results with useful insights. Finally, concluding remarks are drawn in Section 6.

2 Related works

In the field of indoor human behaviour monitoring, diverse studies have been presented focusing on occupancy and social interactions detection. The problem has been addressed by means of diverse hardware and software solutions with their advantages and shortcomings.

From the hardware point of view, the use of electricity meters, Passive InfraRed (PIR) sensors, and environmental (e.g., humidity, temperature, noise) sensors represents a key solution, while from an algorithmic perspective, different approaches have been proposed tailored to the particular issue to be solved. The methods presented in literature can be grouped in two main categories: supervised (with an extensive off-line survey in order to collect training data for the on-line phase) and unsupervised (on-line algorithms discovering target hidden structure/patterns from “unlabelled” data) techniques.

Ruzzelli et al. (2010), Patel et al. (2007), Rosdi et al. (2014), and Barsocchi et al. (2014b) propose approaches based on the identification of several appliances and their use, analysing the equivalent fingerprint given by energy consumptions. This interesting approach is difficult to apply in our scenario, due to the variety of resistive loads that can be observed into a dynamic workplace. In Kim et al. (2009), authors present a system using environmental signals from sensors placed near appliances to estimate their power consumptions. The idea behind these solutions may be summarized as an in-depth monitoring of residential power consumptions. However, in our scenario, the power consumption is quite stable along a workday, with some socialization events occur during short talks and briefing.

In several works (Kleiminger et al. (2013); Chen et al. (2013); Khan et al. (2014)), authors present systems able to perform room occupancy identification. These interesting solutions can infer the occupancy status of the environment, overlooking the social events detection of the person living or working in indoor environments. In particular, in Kleiminger et al. (2013), the authors investigate the suitability of digital electricity meters to be used as occupancy sensors. They have collected electricity consumption data along 8 months, achieving an occupancy detection accuracy of about 80%. In Chen et al. (2013), the authors show a Non-Intrusive Occupancy Monitoring (NIOM) system based on electricity data gathered from smart meters. Mainly, they evaluate the electrical loads consumption by monitoring ground truth occupancy in two homes, trying to identify when each metric’s maximum value at night is exceed during the daytime. In Khan et al. (2014), authors describe a system which use both energy consumption data and environmental information. They evaluate the proposed system in large commercial building, demonstrating its effectiveness and accuracy for occupancy monitoring. In O'Brien et al. (2012) and Yokoishi et al. (2012), authors deal with the room occupancy detection problem using PIR sensor only. In particular, in O'Brien et al. (2012), authors propose an interesting system in which many PIR sensors, are deployed in an apartment. The pervasive dissemination of PIR sensors allows to detect patterns of the overall movements and their occurrences in an hour. Limitations occur when considering blind locations in which PIR sensors are not able to detect a movement and, also, this kind of systems requires a deep survey campaign in order to understand where the sensors must be placed. In Yokoishi et al. (2012) is shown an interesting use of particle filtering of PIR sensor data. It is worth to notice that also in this work a ZigBee-based WSN is presented. Authors test their system in two cases: with motionless human in the room and case with humans coming in and going out. They reach a good overall accuracy but only considering the case of room with motionless human. Otherwise, the occupancy detection ranges from 55% to 65% of accuracy. Furthermore, the work described in Barsocchi et al. (2016b) focuses on room occupancy, analysing environmental and energy consumption time series. Using a stigmergy-based algorithm (Barsocchi et al. (2016a); Palumbo et al. (2015, 2017)), it reaches good performances in many cases despite an initial ad-hoc calibration phase.

Focusing on the detection of indoor social interactions, in Cook et al. (2010), authors investigate the use of smart environment technologies to detect interactions in smart spaces. They tested the system into a real environment, equipped with sensors to provide readings for hot water, cold water, stove usage, power control, lightning control, and motion sensors distributed 1m apart throughout the space. Using a probabilistic approach they evaluate resident interaction reaching good performance. In our case, we investigate the use of similar approaches, trying to reach higher performance in terms of accuracy using a minimal set of smart environment technologies. In Chen et al. (2011), authors present a system able to discover social interactions in real work environments. The system is based on an efficient head and shoulder tracking methods, evaluating in real-time human behaviour and applying a probabilistic model for analyzing their interactions. The accuracy results of this tracking system range from 91.4% to 95.6%, demonstrating a reliable approach. Main drawbacks arise from the computer vision solution used. In fact, in real workplaces, workers may feel this kind of solutions too much obtrusive, by a continuous video recording. In Liu et al. (2014), a system is presented based on a face-to-face proximity estimation model, using bluetooth on smartphones. The system can be used both in outdoor and indoor environments. Using a proximity estimation model analyzing bluetooth received signal strength values, authors show the viability of the solution in their case study. However, the system requires an active interaction of the users with their phones, showing a strong constraint in terms of transparency for the end-user.

In this paper, we propose a system that, exploiting the capabilities offered by the ZigBee technology and the presence of a standard communication middleware (Barsocchi et al. (2014a)), is both able to detect the room occupancy status and to identify social interaction among workers in indoor environments, unobtrusively. To this end, we applied supervised and unsupervised learning techniques in order to test their adaptability to the characteristics of the problem and of the collected data, highlighting advantages and shortcomings of each approach.

3 System overview

In this section, we analyze the chosen solution composed by the developed ZigBee devices. We discuss how the real power consumption has been estimated, how the environmental sensors have been developed, and the developed hardware platform.

In order to send the measured real power and environmental data to the ZigBee network, we developed a ZigBee device exploiting the TI Z-Stack, a fully ZigBee-PRO compliant stack that offers two particular Application Profiles (AP) defined by ZigBee Alliance[1], namely the Smart Energy Profile and the Home Automation Profile. An AP provides a design framework for a specific market sector by defining a set of devices: in ZigBee, a "device" is a software entity comprising the set of properties and functionality of an application that runs on a particular unit called EndPoint (EP). The AP also defines the type of data supported by the application and the operations that can be performed on the data. These definitions are handled in terms of attributes and clusters. ZigBee applications use the concept of "cluster" for communicating attribute values. A cluster comprises a set of related attributes together with a set of commands.

In order to measure the real power consumed by the user in his room, the current waveform is not sufficient. Indeed, when the resistive loads (such as incandescent light bulbs, electric water heaters, etc...) are switched-on, the current and the voltage waveforms are in phase (i.e. the only knowledge of the current waveform is sufficient) and the energy flows to the load. As a consequence, the power is the product of the voltage and the current, at a given time.

However, fridges, electric heaters, washing machines, etc.. also introduce inductive or capacitive components. Most of the energy flows to the load, while the rest is stored and released back afterwards into the mains supply. The current and the voltage waveforms are out of phase and the instantaneous power has a negative part. Moreover, the phase delay is hardly predictable and depends on the specific appliance. In this case, the only knowledge of the current waveform is not sufficient, unless knowing the phase difference. Therefore, in order to measure the current and the voltage values at the same time instant, we use two transformers, namely current and voltage transformers (CT and VT). The former is SCT-013 split core CT by YHDC, the latter is 77DE-06-09 AC to AC adapter by Ideal Power Ltd. The choice of these voltage and current transformers was suggested by an open source project called OpenEnergyMonitor [2] and it is driven by the need to operate within existing buildings without the possibility of changing the existing electrical appliances.

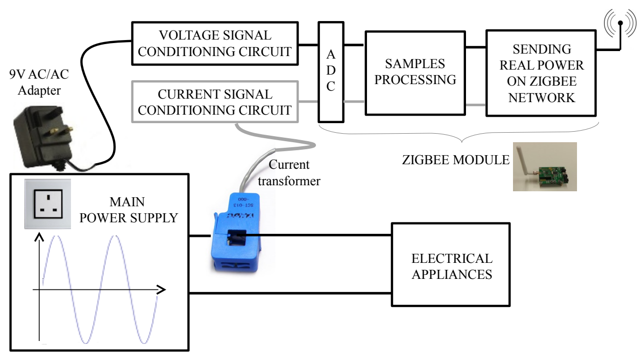

Figure 1: Flow diagram of the energy monitoring system and the ZigBee network node equipped with all sensors.

As shown in Figure 1, both current and voltage signals must be transformed and conditioned in order to be correctly interpreted by the Analog to Digital Converter (ADC). The current conditioning circuit consists of the burden resistor and a biasing voltage divider: the resistor turns the current signal into a voltage signal, while the divider brings the sinusoid upon positive limits. The voltage conditioning circuit consists of a first divider, which scales down the waveform, and a successive biasing voltage divider, which adds an offset to eliminate negative components.

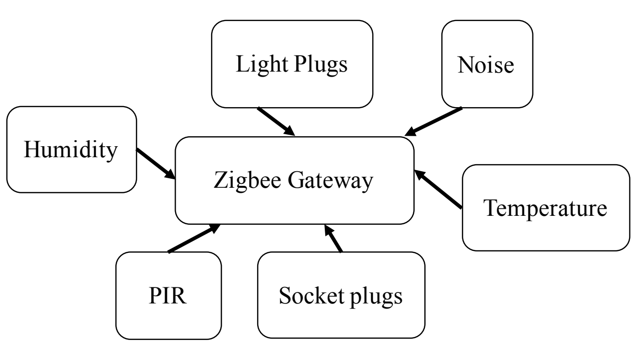

Figure 2: System's components overview

As shown in Figure 2, beyond energy consumption of lights and appliances, rooms have been equipped with some environmental sensors as Passive InfraRed (PIR)-based motion sensor, noise detector, temperature and relative humidity sensor. These sensors have been installed for the purpose of ascertaining occupancy status more carefully and of evaluating occupants well-being. All sensors have digital output and have been completely integrated into the platform. The PIR-based motion sensor is used to sense movement of room occupants. The noise detector is placed in the center of the room and triggers an output signal when environmental sound exceeds a fixed decibel threshold. Temperature and relative humidity sensors are fully integrated on a unique chip and it is based on a polymer humidity capacitor and a NTC thermistor. Data is sent to MCU on output pin via 1-wire communication. Regarding motion and noise detectors, the microcontroller unit reads the value (HIGH or LOW) from a specified digital pin every 23 milliseconds. After about 6 seconds the number of time K that the measured values exceed the threshold is reported (eq. 1).

$$K = \sum_{i=1}^{N} b[i]$$
$$b[i] = \begin{cases} 1 & \text{if the value exceeds the threshold} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

So, also in this case, the minimum timer expiration is fixed to 6 seconds, while the delta value is fixed to 1. It is important to note that these values do not represent an absolute amplitude quantity, but indicates the persistence of that kind of data values considered over the time. Temperature and relative humidity are read once a minute; the minimum timer is fixed to 60 seconds, while delta value is 1^oC for the temperature and 1% for the humidity. The maximum timer expiration is set to 300 seconds for all the endpoints.

4 Methods

Our aim is to determine the room occupancy status and to detect socialization events into the monitored room. With the term occupancy we refer to the possibility of determining if a room is occupied from at least one person within a time interval. Instead, a socialization event is defined as the status different from the usual activity (empty room or room within expected number of employees) being performed by the workers. In this work, the room occupancy and social interaction identification is implemented using two different approach: supervised learning (classification task) and unsupervised techniques (clustering).

Regarding supervised learning techniques, a classification task consists in assigning a class to a given input object. Generally, an object is a vector containing features which allow a characterization of the input. We chose as features the mean and standard deviation of each sensor computed using a time window of 5 minutes. We have evaluated the performance of the proposed system by using three different classification algorithms: Logistic regression, IbK and Random Forest. The considered methods belong to different classes of learning systems. In particular, Logistic Regression and IBK belong to statistical learning group. Random forest, instead, comes from rule-based learning group.

In detail, Logistic regression is a well–known technique based on linear regression. The idea of logistic regression is to make linear regression producing probabilities (Friedman et al. (2000)). When using linear regression for binary classification, we evaluate a linear function, applying a threshold in order to distinguish 0 or 1 response. In order to generalize this binary approach to more than two classes, we can use a separate regression for each class, setting output to 1 for instances belonging to that class and 0 otherwise. Given an unknown test example, the class with the largest output must be chosen. That would give us n regressions for a problem where there are n different classes.

In this work, we evaluate also the implementation of a different supervised technique called IbK, based on k–nearest neighbours. This method is memory–based and does not require a model construction (Aha et al. (1991)). The principle behind IbK is to discover the k (we consider $k = 1$) closest training examples in the feature space with respect to the new sample. The training phase of this algorithm consists in storing the features and the class label of the training objects. In the classification phase, an unlabelled object is classified by assigning the most frequent label among those of the k training samples nearest to it. During test, new objects are classified based on a voting criteria: the k nearest objects from the training set are considered, and the new object is assigned to the class most common amongst its k nearest neighbours. These methods usually allow good results when there are not regular separation of the decision boundaries. Our dataset seems fit with this definition.

Considering this aspect, a natural step over the linear classification learners is the random forest (RF) algorithm. It is based on decision trees and it is considered as an improvement of the bagging model. Moreover, it allows a decorrelation between trees and, consequently, between their predictions (Breiman (2001)). The idea behind this method is to make a tree in which each internal node is labelled with an input feature. The arcs from a node representing a particular feature are labelled with each of the possible values of that feature. Each leaf of the tree is labelled with a class or a probability distribution over the classes. Random forest model is a non–parametric model and, consequently, it does not need any a priori assumption; it is able to face complex input–output relations; it is robust to errors in labels and outliers.

Finally, we discuss a completely different category of machine learning approach: unsupervised classification techniques (clustering). These methods are not based on inquiries, personal interview, or extensive campaigns of data labelling for ground-truth construction. Furthermore, supervised or semi-supervised learning models, require an extensive data collection campaign and ground truth gathering in order to train the classifiers. In our study, this aspect can be fundamental. We will discuss in section 5 if the advantages, in term of results, may be justified. In order to use these methods, our approach relies on a minimal set of domain-based knowledge, such as the number of workers assigned to each room and the fact that, during each day, the majority of time spent by the workers is on performing usual daily activity with respect to have social interactions. This consideration has a two-fold consequence. We can infer about room occupancy status and about social interactions detection.

In this work, the unsupervised clustering techniques implemented are: K-medoids, K-means, Hierarchical clustering and Fuzzy C-means. These four methods have a fixed number of clusters: 2 cluster when the goal is room occupancy detection, 3 cluster when our interest rely on social interactions identification.

The idea behind clustering methods is grouping similar data, basically separating them from the dissimilar data. Similarity is evaluate on the distance measure between groups of data. This distance can be evaluated using several metrics (Manhattan, Euclidean, Cosine, Mahalanobis, Hamming, and more). Mainly, there are two kinds of clustering methods: soft or hard clustering. The first ones are unable to distinct boundaries and Fuzzy C-means belongs to this category. Each data point belongs to different separated clusters using a probability or likelihood function (Dunn (1973)). The second ones are able to well distinguish boundaries, each data point can belong to one cluster completely or not. K-means (KM) (MacQueen (1967)), K-Medoids (Kaufman et al. (1987)), and Hierarchical methods (Sibson (1973)), belong to this category.

K-means is a well-known, fast and simple to implement, clustering algorithm for partitioning a dataset in k, fixed, different clusters. It also has an $O(n)$ computational time complexity. The main drawback occurs regarding the form and scattering of clusters, especially when clusters are overlapped. Due these drawbacks, Fuzzy C-means clustering was introduced in literature. Fuzzy C-means algorithm is the most popular fuzzy clustering techniques. For each data point belonging to given number of cluster, it gives and update a membership value. In this way, each data point can belong to all clusters, according to these membership values. In the k-means and k-medoids approaches, each cluster is associated with a unique cluster representative. The computation of an objective function becomes linear in N.

Like K-Means, K-Medoids takes the number of clusters k as input, but differs in three ways. First, K-Medoids methods attempt to minimize dissimilarity directly, which reduces sensitivity to outliers. Second, instead of centroids, K-Medoids uses medoids, which are objects from the input data that act as cluster

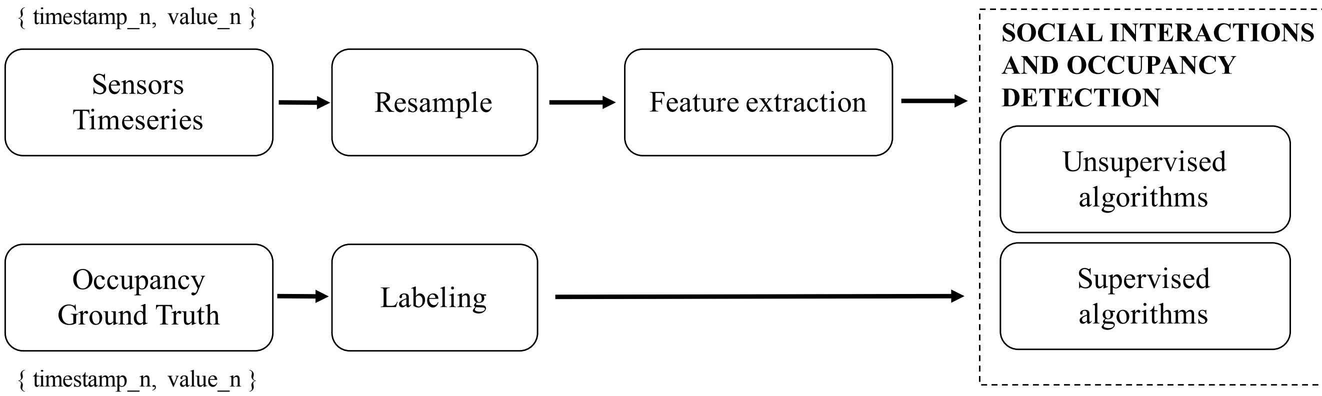

Figure 3: Data processing workflow

reference samples. Finally, K-Medoids only requires to formulate a distance measure between input elements, without requiring to compute a mean. Hierarchical cluster algorithms combine data objects into clusters, those clusters into larger clusters, and so forth, creating a hierarchy. We also consider this method despite a $O(n^2)$ or $O(n^2 log(n))$ complexity and, generally, more of the computation time is spent in pre-computing a dissimilarity matrix to store distances between each pair of objects (Gamblin et al. (2010)). Considering the small size of the dataset proposed in this work, we can utilize an hierarchical approach, despite the drawback of the worst computational time complexity.

Our dataset presents characteristics useful for understanding which algorithm will lead us to better results. Analysing our goals, room occupancy and social interactions detection, we can affirm that the dataset contains well separable clusters. In fact, time series gathered from the different transducers present a threshold form: lights are switched on or off, humidity has substantial different values considering night time and day time, PIR transducer has an intrinsic binary behaviour. Only the sockets plugs sensor has a different characteristic. In fact, when a room is occupied by several workers (more than one), the energy consumption will be significantly different. For all these reasons, these four methods mentioned will lead us to quite close performances in terms of overall accuracy, but we will obtain strong performances in terms of Cohen's coefficient (K) observing room with more workers than one.

5 Experimental setup and evaluation

The proposed system has been deployed at the National Research Council (CNR) Area in Pisa, Italy. The building covers around 45 thousands square meters, it is one of the largest research areas in Italy and over 1500 employees frequent it every workday. In order to infer the occupancy status of the monitored rooms and socialization events, we analysed data coming from all installed sensors: motion detectors, power meters, lights status and noise sensors. We collected data in a period of three weeks in an office environment, involving three heterogeneous offices that included one office with a single occupant, one double occupancy and one triple-occupancy room. Every room is fully equipped with the system shown in Figure 1. Such different configurations allowed us to capture a diversification of patterns in the offices usage. The PIR-based motion sensor reports a data sample only when a movement is detected in the monitored room area. Noise detector, instead, produces a data sample at regular intervals, indicating not the intensity but the persistence of noise measured in a time interval. Power meter produces a scalar value that represents a real-power consumption in Watt of the entire monitored room in a time interval. We also installed a power meter on the lights from which we can infer their status in the room. For each sensor we have a time series of data in the format $\{timestamp_n, value_n\}$.

The workflow of data processing is shown in Figure 3. A first step of data processing is required in order to obtain a time series of samples with regular interval, considering the data collected during the three weeks. A feature extraction task processes the time series obtained from the data preprocessing step to provide efficient data characterization. The algorithm evaluates the mean value and the standard deviation for all the samples contained in each time slot of 5 minutes. Therefore, the time series is divided into chunks of 5 minutes, the mean value and the standard deviation of the samples included into each time slot is evaluated. The algorithms are statically configured in order to discriminate only three sets of data samples, which should represent, according to our expectation, empty room, usual room working activity and socialization activity. We assume that the cluster resulting with the greater number of samples represents the empty room cluster, the intermediate number the usual-activity cluster and the smaller number the socialization-activity cluster.

We collected over the experiment period a ground truth by means of cameras recording the events of entrance and exit of people for the monitored rooms.

Ground truth data also follows the preprocessing step described before. Sensors and ground truth time series are also provided as input to a supervised occupation detection algorithm, in order to detect the occupancy status of the monitored offices (presence or absence) into each time slot.

5.1 Evaluation metrics

In order to compare different methods and outputs, we compute the overall accuracy, defined as:

$$Acc. = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

being TP, TN, FP, and FN, the true positive, true negative, false positive, and false negative, respectively, considering correct predictions are true and wrong predictions as false. Accuracy is the percentage of correct predictions with respect to the total number of samples. In this work we present two different approaches for achieve the room occupancy and the social events detection: supervised and unsupervised techniques. Regarding results obtained using supervised approaches we also show the Kappa statistic defined as:

$$K = \frac{\mathrm{totalAccuracy} - \mathrm{randomAccuracy}}{1 - \mathrm{randomAccuracy}}$$

Furthermore, we define three different classes that provide us a match between the ground truth collected by the cameras and the correspondent results provided by the algorithms. Each output sample was considered as a point belonging to one of three classes: values equal to 0 represent empty room class, values of 1 belong to normal condition class and values of 2 to the social event class. We define the normal condition of each room when it is occupied by a maximum number of workers assigned to that room.

It is worth to notice that in unsupervised approaches is impossible to label the meaning of the different clusters. Since we are interested in social events and room occupancy detection, the idea behind our prosed system is consider cluster dimensions. It is reasonable that biggest cluster means class 0 because, considering our dataset composed by data gathered in a journey, a worker is into the office no more than 10 hours a day. Instead, the smallest cluster represent social event class, because generally social events sporadically occur.

5.2 Supervised approach

In this work, we present results of room occupancy status and social interactions detection using the three different supervised method described in Section 4, namely Logistic, IBK, and Random Forest, in order to demonstrate that both the selected features and the chosen inputs allow to perform a well-posed supervised learning problem.

It is worth noticing that, in terms of room occupancy, it is reasonable to think that only the information collected by PIR sensors could be significantly enough to reach a good accuracy. Nevertheless, in certain time slots, the PIR sensor does not detect any movement, although the room was occupied by at least one person. This is the case of workers that, once entered into their office, pass most of their time sitting at their workstation without moving considerably. This can be seen, indeed, in Figure 4, showing the PIR output, after the feature extraction block, as well as the Ground Truth from one room for approximately 12 hours of a working day. In the figure we can see that no input is given by the PIR sensors in most of the period labelled as “occupied” in the ground truth. For this reason, the full set of available sensors is needed.

Table 1 shows the obtained results, considering the entire dataset including PIRs. As mentioned before, the complete dataset performs better than the dataset composed of only PIR sensors, both in terms of accuracy and kappa values, despite the chosen algorithm. Even if the performance obtained by PIRs only can be considered acceptable, in emergency situation a better accuracy is needed.

From the algorithmic point of view, the best performance are reached using Random Forest, in terms of both accuracy and kappa improvements. In order to justify such a result, we recall a key aspect about Random forest approach. It belongs to the class of ensemble methods, based on a combination of tree predictors. Each tree is composed using a subsampling of the training set. Combining outputs from each tree the algorithm is able to improve the generalization performance and avoid the overfitting problem. Our dataset presents a non clear separation between values belong to different classes. Consequently, a task of classification using decision tree methods show higher performances.

Regarding social interactions detection, Table 2 shows the confusion matrices generated by using the supervised algorithms above-mentioned. Here, each column counts the instances in a predicted class (i.e., 0, 1 and 2), while each row represents the instances in an actual class. Thus, the diagonal cells (gray) count the number of correct classifications made for each class, and the off-diagonal cells (white) count the errors made. We also show for each classifier the overall accuracy and the kappa statistic. As shown in the table, values of accuracy are comparable for the three room typologies, and in any case always greater than 93% for all classifiers. Random Forest algorithm gets the best results, with an overall accuracy of around 95% and kappa of around 83% on average.

5.3 Unsupervised approach

As discussed in Section 4, the rationale behind the application of unsupervised approaches is represented by the absence of ground-truth construction and labelling. In order to compare the obtained results with the above-described performance of the supervised approach, we

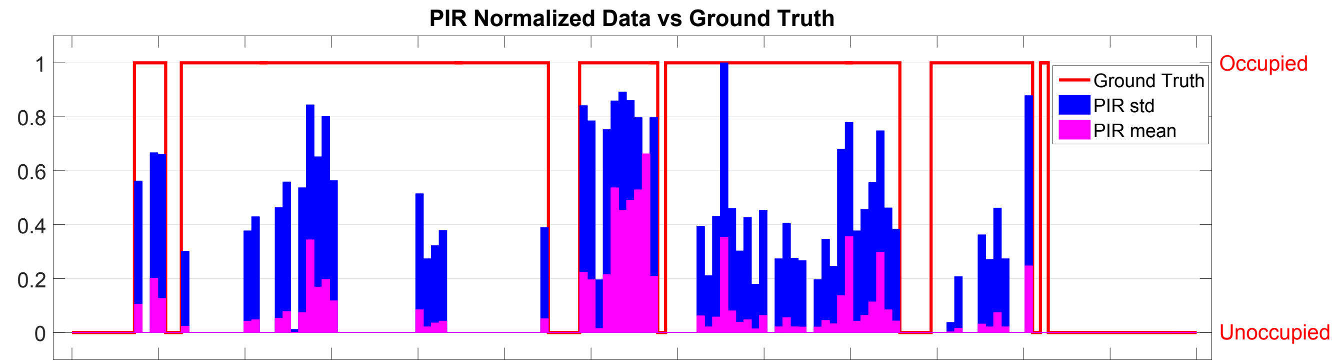

Figure 4: PIR Normalized Data vs Ground Truth for room B in a generic workday

Table 1 Logistic, IBK and Random Forest occupancy detection classification results

		Logistic		IBK		Random Forest	
Dataset	Room	Acc.	K	Acc.	K	Acc.	K
Full	A, three workers	97.2	92.7	96.9	92	97.8	94.5
	B, two workers	96.8	90.5	96.2	88.3	97.3	91.8
	C, one worker	96.3	78	96.2	78.9	97.1	84
PIR	A, three workers	95.8	88.9	95.8	88.9	96.5	91
	B, two workers	90.9	67.3	91	67.7	91.4	69.4
	C, one worker	94.6	63.6	94.8	66	95.1	68.4

Table 2 Logistic, IBK and Random Forest social interactions classification results

		Logistic					IBK					Random Forest				
		activity predicted			Acc. [%]	K [%]	activity predicted			Acc. [%]	K [%]	activity predicted			Acc. [%]	K [%]
Room	GT	0	1	2			0	1	2			0	1	2		
A 3 workers	0	3978	75	2			3966	83	6			3964	89	2		
	1	62	1128	22	95.1	87.8	74	1060	78	93.7	84.4	24	1155	33	95.4	88.7
	2	8	97	101			4	97	105			2	100	104		
B 2 workers	0	4261	112	2			4278	86	11			4275	95	5		
	1	53	801	31	94.3	83.3	104	693	88	93.0	79.0	45	795	45	94.9	85.1
	2	4	106	103			10	82	121			2	83	128		
C 1 worker	0	4863	65	8			4830	98	8			4865	63	8		
	1	125	223	18	94.4	67.3	92	218	56	93.9	66.9	82	240	44	95.3	74.1
	2	17	71	83			10	65	96			6	50	115		

Table 3 K-medoids, K-means, Hierarchical clustering and Fuzzy C-means room occupancy detection results

		K-means		Hierchical		Fuzzy C-means		K-medoids	
Dataset	Room	Acc.	K	Acc.	K	Acc.	K	Acc.	K
Full	A, three workers	97.0	92.4	97.0	92.3	97.1	92.4	97.0	92.3
	B, two workers	90.3	64.4	97.0	91.0	96.7	90.1	96.8	90.2
	C, one worker	93.1	52.9	92.9	50.6	93.0	52.7	93.0	52.7
PIR	A, three workers	94.1	83.7	96.4	90.5	94.2	84.1	94.3	84.4
	B, two workers	88.9	57.8	91.6	70.2	88.8	57.2	88.7	57.0
	C, one worker	94.8	65.7	95.5	71.4	94.2	59.6	94.2	59.7

Table 4 K-medoids, K-means, Hierarchical clustering and Fuzzy C-means social-event detection results

		K-Means					Hierarchical					Fuzzy C-Means					K-Medoids				
		activity predicted			Acc. [%]	K [%]	activity predicted			Acc. [%]	K [%]	activity predicted			Acc. [%]	K [%]	activity predicted			Acc. [%]	K [%]
Room	GT	0	1	2			0	1	2			0	1	2			0	1	2		
A 3 workers	0	3948	18	89			3944	21	90			3949	20	86			3949	29	77		
	1	36	746	430	86.4	67.4	36	625	551	84.0	62.0	38	762	412	86.6	67.7	38	836	338	87.8	70.6
	2	15	157	34			17	162	27			11	169	26			11	172	23		
B 2 workers	0	4255	93	27			4236	51	88			4254	98	23			4254	101	20		
	1	53	510	322	90.3	72.1	24	455	406	86.2	60.9	43	556	286	91.0	74.2	44	602	239	91.8	76.3
	2	4	32	177			0	188	25			4	38	171			4	41	168		
C 1 worker	0	4815	88	33			4809	84	43			4815	88	33			4816	88	32		
	1	101	164	101	92.3	57.6	99	160	107	92.2	57.4	114	165	87	92.3	56.8	119	167	80	92.3	56.6
	2	21	76	74			21	71	79			24	76	71			26	76	69		

present in Table 3 and 4 the obtained results in the same way.

Regarding the room occupancy detection, Table 3 shows a comparison between results reached using the full dataset and PIR only. We can observe a similar overall accuracy despite the method chosen, higher than results obtained using PIR only in room occupied by three workers and two workers. We show the obtained performance in terms of accuracy and kappa statistic. We obtain a lower kappa in the evaluation of room occupied by one worker due to the fact that, in general, a worker alone in a room does not perform movements inside the environment, excluding entry and exit. Instead, in a room occupied by more than one worker, PIR sensor is triggered several times as consequence of workers' movements from a desk to another.

Finally, Table 4 shows the results obtained for the social interactions detection scenario. The common aspect of these four methods is the fixed number of clusters, i.e. 3. The overall accuracies are quite close, in a similar way with results observed in the room occupancy scenario. We can observe an overall accuracy ranging from 84% to 92.3% and high kappa values for 3-workers and 2-workers scenarios. These results enforce the considerations made in Section 4. In case of social interactions, the energy consumption time series becomes less significant (for example, phenomenons of personal computer energy saving are less frequent). Furthermore, also observing sub-matrices 2x2 composed by classes 1 and 2, it arises a significant reduction of the number of social events. This aspect leads unsupervised algorithms to make more errors with respect to scenario A and B, in which same sub matrices are composed by a significant large numbers of samples.

6 Conclusions

In this paper, we presented a system able to detect the room occupancy state and social interactions inside workplaces. The system has been deployed on three rooms of the CNR research area in Pisa. This system is particularly useful for emergency situation during which is important to know when a room is occupied or not and, furthermore, for the identification of social interactions. This knowledge can prevent phenomenons of depression and social marginalisation by monitoring them over the long period.

The proposed system, exploiting the capabilities offered by the ZigBee technology and the presence of a standard communication middleware, is both able to detect the room occupancy status and to identify social interaction among workers in indoor environments, unobtrusively. To this end, we applied supervised and unsupervised learning techniques in order to test their adaptability to the characteristics of the problem and of the collected data, highlighting advantages and shortcomings of each approach.

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