A low-cost BLE-based distance estimation, occupancy detection and counting system

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***Abstract*—This article presents a low-cost system for distance estimation, occupancy counting, and presence detection based on Bluetooth Low Energy radio signal variation patterns that mitigates the limitation of existing approaches related to economic cost, privacy concerns, computational requirements, and lack of ubiquitousness. To explore the approach effectiveness, exhaustive tests have been carried out on four different datasets by exploiting several pattern recognition models.**

***Index Terms*—Bluetooth Low Energy (BLE), Distance estimation, Occupancy Detection, Occupancy Counting.**

I. Introduction

On the basis of many Internet of Things (IoT) scenarios, particularly smart buildings, smart cities, and Human Activity Recognition (HAR) solutions, we need systems for automatically detecting people's presence, estimating their number, and measuring interpersonal distance [1]–[4].

Such systems can be categorized in: a) device-free (e.g., [5]) and b) not device-free (e.g., [6]). Not device-free solutions are based on people's presence recognition by exploiting radio signals emitted by devices, which they are wearing or carrying in their pockets/bags, and received by another device, which is integrated within the target environment. However, if people entering the target environment do not use a specific device and related software, their presence cannot be recognized. On the contrary, device-free solutions are based on the study of smart metrics related, for example, to radio signal patterns, CO_2 sensors, sound-based or video-based technology.

Several alternatives are presented in the literature for device-free solutions. Yang et al. [7] presented a platform for occupancy sensing that makes use of the Channel State Information (CSI) measurements. Depatla et al. [8] propose a methodology based on understanding patterns related to the people signature on the transmitted radio signals. Zou et al. [5] presented an occupancy detection methodology that, given CSI data, measures the shape similarity between adjacent time series CSI curves. Chen et al. [9] proposed an occupancy detection system by analyzing the changes in statistical metrics of power consumption data. Akbar et al. [10] presented an occupancy detection system based on electricity consumption by exploiting machine learning algorithms. However, most of the previous solutions present some limitations, mainly related to their economic costs (requiring specific dedicated HW) and computational requirements. To overcome such limitations, this paper presents an easily accessible occupancy detection and counting platform based on a mobile Android application and Bluetooth Low Energy (BLE) devices, which can also be exploited for distance estimation. The main characteristics of the proposed approach are: it is low-cost and not invasive; it requires low computational resources and no dedicated hardware; it can be easily integrated into different smart scenarios. The rest of the paper presents the methodology (Section II) and discusses experiments (Section III) before drawing concluding remarks (Section IV).

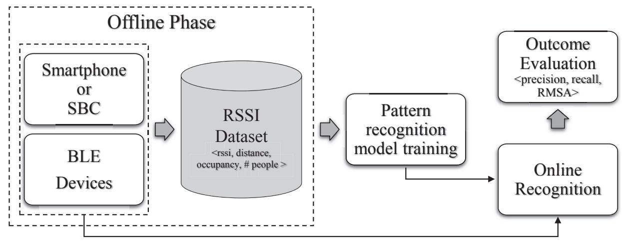

Fig. 1. Schematic view of the proposed methodology.

II. Methodology

The proposed methodology associates specific RSSI[1] patterns to the number of people, their presence within an environment, and receiver-emitter distance. It consists of three phases (Fig. 1): (i) RSSI data collection, related to the communication between BLE emitters and smartphone/Single Board Computer (SBC) receiver; (ii) training of pattern recognition models; (iii) evaluation of pattern recognition models.

The methodology makes use of a communication architecture that stores data perceived by the emitting devices into a remote database, passing through an intermediate receiver represented by a smartphone or SBC. The goal is to study the changes in the radio signal patterns generated by the emitters to identify the most appropriate recognition/regression model to estimate the environment status (i.e., environment occupancy, number of people, and the distance between emitters and receiver). The architecture relies on a BLE communication initially established between the emitters and a single receiver. Subsequently, the receiver stores the data internally by performing periodic synchronization with the remote server. As emitters we use Nordic Thingy™ 52 (nRF6936) nodes. They are compact, power-optimized, multi-sensor devices designed for collecting environmental data of various types. For example, they can sense movement, orientation, temperature, humidity, air pressure, light, color, air quality, and sound. The

This research work has been partially supported by the project Dipartimenti di Eccellenza 2018-2022 funded by the Italian Ministry of Education, Universities and Research (MIUR).

[1]The Received Signal Strength Indicator (RSSI) is a power level measurement associated with the received radio signal after antenna and cable loss. Higher values of RSSI correspond to the stronger received signal.

Timestamp	Mac_{Addr_1}	Mac_{Addr_2}	Mac_{Addr_3}	Mac_{Addr_4}	...	Mac_{Addr_n}	Occupancy	Nr. People
26/08/2020 09:56:45.005	-51	-65	-80	-100	...	-35	true	2
26/08/2020 09:56:45.010	-41	-55	-70	-90	...	-45	true	4
...	...	...	...	...	...	...	...	...
26/08/2020 10:00:00.000	-37	-49	-65	-70	...	-35	false	0
Distance (cm)	25	500	100	300	...	600		

TABLE I
RSSI MEASUREMENTS DATASET FORMAT

data transmission rate towards BLE-enabled receivers is fixed at a frequency range between 5 Hz and 200 Hz. Their position in the environment can be arbitrary, with the only restriction that the location cannot vary between the offline and online phases shown in Fig. 1. The BLE receiver can be implemented by using different devices (e.g., mobile phones, laptops, and SBC). In our current architecture, the receiver is an Android OS-based device. This choice has been primarily taken due to its compatibility with several pattern recognition libraries (e.g., Keras, Tensorflow, or Weka).

A. *Offline data collection*

During this phase, the receiver perceives, at a fixed frequency, the measurements collected by the Thingy sensors distributed in the environment associating to each of them a timestamp and the corresponding RSSI value. The data are then transmitted to the server. Finally, at each timestamp, each RSSI measurement is associated with i) the number of persons present in the environment and ii) the distance between the emitter and the receiver. The final RSSI measurements dataset format is represented in Table I. Column MAC_{Addr_i} refers to the RSSI measurements related to the emitter with MAC address i. Column occupancy is false when the number of people in the environment is 0. The *distance* row refers to the distance between the emitters i and the receiver. RSSI measurements represent the input (*predictors*) for the pattern recognition models used during the online evaluation. Instead, the occupancy state and the number of people into the environments are the target outcome (*outcome variables*) we want to predict.

B. *Pattern recognition models*

Collected data are used to study the following scenarios:

1) estimation of the distance between an emitting and a receiving device (not device-free);
2) recognition of the occupancy status of the environment (device-free);
3) estimation of the number of people inside the environment (device-free).

Initially, collected data are preprocessed by segmenting each emitter's RSSI measurements in one second time window segments. Subsequently, from each segment, we extract a set of features (e.g., average, min, max, std, mode, median, var, frequency coefficients, etc.) belonging to the temporal, statistical, and spectral domains, as presented in [11]. In particular, a one-second time window of RSSI measurements (acquired with a 200 Hz frequency) related to a single emitter is represented by 159 features. At the end, we have two datasets: one composed of raw data directly collected from the emitters (raw dataset in the following), and a second one obtained through the preprocessing phase previously described (features dataset in the following). Both of them are used in the analysis reported hereafter for each of the considered scenarios.

1) Distance estimation: Unlike scenarios 2 and 3, the distance estimation is based on the analysis of the signals emitted by every single emitter and not on the whole group of emitters included in the environment. Moreover, since it is an estimation problem, we use different regression models. The regression models are trained by using both the raw dataset (univariate regression) and the features dataset (multivariate regression).

In our case, univariate regression analysis on the raw dataset presents one dependent variable (outcome) and one independent variable (RSSI values). Instead, the multivariate regression analysis on the feature dataset presents one dependent variable (outcome), and multiple independent variables (features) [12]. In the first case, the model returns the distance estimation every 5 ms (200Hz). Instead, in the second case, it returns the distance estimation every one second. We assume significant changes in position requires a higher amount of time. The models accuracy is measured in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), calculated as shown in Equations 1, and 2 [13].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|y_i - x_i|)^2} \quad MAE = (\frac{1}{n})\sum_{i=1}^{n}|y_i - x_i| \quad (1)$$

were x_i identifies the actual outcome variable, y_i the estimated outcome, and n the number of testing samples.

2) Occupancy Detection: It represents a binary classification problem, where *false* means the environment is empty, and *true* that there is at least one person in the environment. Therefore, such a scenario aims to estimate the occupancy status over a time window of one second using only the features dataset generated from all the emitters distributed in the environment. The results of such a classification problem are evaluated by using the following quality metrics [13]:

$$\begin{aligned} Precision &= \frac{TP}{TP+FP} \quad & Specificity &= \frac{TN}{FP+TN} \\ Sensitivity &= \frac{TP}{TP+FN} \quad & Accuracy &= \frac{TP+TN}{P+N} \end{aligned} \quad (2)$$

3) Occupancy Counting: Finally, occupancy counting represents an estimation problem that aims to identify the number of people in the environment. This scenario is tested on both the raw and the features dataset and evaluated similarly to the distance estimation scenario. The only difference concerns the simultaneous use of the signals generated by multiple emitters.

C. *Training and validation approach*

For each scenario, the RSSI (raw or features) measurement datasets are initially divided into training (75%) and testing

Dataset ID	# of Emitters	Use Case Scenario	Emitters Position	Receiver Position	min # of People	max # of People	min distance (cm)	max distance (cm)	# of samples	Size (Mb)
1	6	distance baseline	fixed	fixed	-	-	25	500	892k	261
2	6	distance estimation	mobile	fixed	1	1	25	500	122k	42
3	5	occupancy detection	fixed	fixed	0	6	100	600	372k	302
4	5	occupancy counting	fixed	fixed	0	6	100	600	1483k	181

TABLE II
DATASETS CHARACTERISTICS.

(25%) partition by following the hold-out procedure. On the training partition, we apply a k-fold cross-validation procedure with $k = 3, 5$, and 10. Finally, we use the testing partition to further stress the used models. In the end, the procedure returns the above-mentioned evaluation metrics.

III. EXPERIMENTAL RESULTS

An extensive set of experimental analyses has been conducted to evaluate the pros and cons of the adopted regression models in the context of the target scenarios.

A. Characteristics of the analyzed datasets

Table II shows the characteristics of the considered datasets. Columns one to five show the dataset ID, the number of BLE radio signal emitters distributed in the environment, the considered use case scenario, the emitter's position, and the position of the receiver. Columns six to nine show the lowest and highest number of people inside the environment during the analyzed period and the minimal and maximal distance between the emitters and the receiver. Finally, columns ten and eleven show the number of samples and the size of the dataset. In dataset 1, emitters and receiver are not subject to movements. Instead, in dataset 2, the emitter is worn by a subject that moves inside the environment into a range of 5 meters from the receiver. Finally, datasets 3 and 4 are subject to people's presence inside the environment and their number. In datasets 3 and 4, the environment occupants are not aware of the emitters and receiver positions and cannot touch or move them. Overall, datasets 1-4 present 5 hours of collected data. The datasets are intended to study the effect people (presence and movements) have on radio signal distribution.

B. Distance estimation

Since radio signal transmission highly depends on the environment characteristics [14], we limited the tests on this scenario to a maximum distance of 5 meters between the receiver and the emitters. Seven different regression models have been tested over datasets 1 and 2 by exploiting both the raw RSSI data and the corresponding temporal, statistical, and spectral features. In dataset 1, the positions of emitters and the receiver are fixed. Instead, in dataset 2, one subject wearing the emitter on the wrist moved forward, backward, and around the receiver to recreate the most realistic human behavior. The evaluation has been performed on three different distance range: a) 0-5 meters, b) 0-3 meters, and c) 0-2 meters. Table III shows the achieved results in terms of RMSE, and MAE (values are in centimeters), while estimating the distance between the emitter and the receiver. As clearly visible, the Random Forest model achieved the lowest RMSE/MAE value in both raw and feature datasets. The second most performing model was Gradient Boosting. Overall, we achieved an RMSE on raw RSSI data of 51 cm in the range 0-5 m, 17 cm in 0-3 m,

Farthest distance	Regression model	Raw Data RMSE	Raw Data MAE	Features RMSE	Features MAE
5	Gradient Boosting	51	31	57	33
M	Random Forest	51	31	55	28
e	Linear	74	58	104	79
t	Ridge	74	58	69	45
e	RANSAC	84	54	113	86
r	Bayesian	74	58	233	158
s	TheilSen	78	54	96	70
3	Gradient Boosting	17	12	30	15
M	Random Forest	17	12	25	8
e	Linear	27	22	80	60
t	Ridge	27	22	60	39
e	RANSAC	28	21	85	59
r	Bayesian	27	22	229	171
s	TheilSen	29	21	89	65
2	Gradient Boosting	12	9	30	15
M	Random Forest	12	9	25	8
e	Linear	22	16	80	60
t	Ridge	22	16	60	39
e	RANSAC	43	26	82	59
r	Bayesian	22	16	229	171
s	TheilSen	24	18	89	65

TABLE III
DISTANCE ESTIMATION RESULTS (DATASET ID=1 AND ID=2).

and 12 cm in 0-2 m. Moreover, in terms of MAE, the features dataset performed better than raw data: 28 cm (range 0-5 m), 8 cm (range 0-3 m), and 8 cm (range 0-5 m). Furthermore, these models' most essential characteristics regard the reduced memory and computation requirements, making them very suitable for mobile computing and hardware-constraint devices. This is because regression models define uni/multivariate functions, which from the mathematical point of view, represent an easily computable series of sums of products.

C. Occupancy detection

Occupancy detection is a challenging problem, mainly due to the multitude of activities and positions that people take within an environment. During the data collection phase of datasets 3 and 4, tests were carried out in a university classroom (8.8 m x 8.6 m) with 15 study stations (chairs + tables) involving six different subjects. One female (29 years, 1.58 m height) and five males (25-29 years, 1.75-1.95 m height) were involved in the experiment. Subjects entered and left the environment in an undefined order with the only constraint that they must stay in the environment at least for one minute. Besides, the following environmental situations were recreated: i) all standing still, ii) all standing in motion, iii) all seated, and iv) some standing in motion and some sitting. Table IV presents the achieved results over datasets 3 and 4. On both datasets, five different emitters were used. The datasets are made up of 66% non-empty environment instances and 34% of empty environment instances. Tests were performed over five different well-known classification models[2]. Columns

[2]k-Nearest Neighbor (kNN), Weighted kNN (WkNN), Linear Discriminant Analysis (LDA), Quadratic LDA (QLDA), Support Vector Machine (SVM)

two to five show results in terms of specificity, sensitivity, precision, and comprehensive accuracy.

Model	Specificity	Sensitivity	Precision	Accuracy
kNN	98.72%	99.10%	99.10%	99.10%
WkNN	98.29%	99.02%	99.03%	99.10%
LDA	99.83%	99.70%	99.70%	99.70%
QLDA	99.78%	99.77%	99.77%	99.77%
SVM	99.82%	99.86%	99.81%	99.82%

TABLE IV
OCCUPANCY DETECTION RESULTS (DATASET ID=3 AND ID=4).

Overall, the SVM model with a linear kernel achieved the most noticeable results. Such a model, among all the other models, requires higher computational capabilities; however, Keras library provides a Quasi-SVM model implementation for Android-based mobile devices. By verifying the generated errors in detail, we observed that the incorrectly classified samples are related to the situation in which people inside the environment are all seated, independently by their number. Moreover, we performed the same test by applying a partitioning of 50% training and 50% testing. Again, the achieved accuracy of the classifiers was approximately 98.5%. This means that the features used to characterize RSSI measurements pattern variation can efficiently separate the two categories understudy.

D. Occupancy estimation

Table V presents the results obtained on raw and features datasets. The outcome is an estimation of the number of persons into the environment. The lower is the RMSE, the higher is the estimation accuracy. Again the Random Forest regression model achieved the best results on the features dataset. In particular, the proposed occupancy counting system, given a set of features identifying a one-second time window of RSSI measurements, estimates the number of people into the environment with an RMSE of 0.5 and an MAE of 0.3.

Regression Model	Raw Data		Features	
	RMSE	MAE	RMSE	MAE
Gradient Boosting	0.9	0.6	0.5	0.3
Random Forest	0.7	0.4	0.5	0.3
Linear	1.4	1.0	1.3	1.0
Ridge	1.4	1.0	2.5	4.2
RANSAC	1.8	1.3	3.3	3.3
Bayesian	1.4	1.0	2.1	2.1
TheilSen	1.9	1.2	2.0	1.8

TABLE V
OCCUPANCY ESTIMATION RESULTS (DATASET ID=3 AND ID=4).

Instead, by using the raw dataset, we achieved an RMSE of 0.7 and an MAE of 0.4. As for the occupancy detection scenarios, the estimation error is amplified when all people inside the environment are sitting down.

E. Energy consumption

The proposed architecture was evaluated from the energy consumption point of view in terms of average RAM, memory, and battery consumption for both emitter (Nordic Thingy 52) and receiver (Oneplus 6). Nordic devices can efficiently compute for more than seven days without reducing the sampling frequency. The receiver presents the following average consumption values: 54 mAh concerning battery, 122 Mb/h of memory, and 59 Mb/h of RAM. Furthermore, all scenarios were tested by reducing the sampling frequency of the emitters. With frequencies higher than 35 Hz, the results did not change. However, by reducing the sampling frequency under such a threshold, the results' accuracy quickly degrades. Moreover, we found challenging the use of some types of receivers, such as Honor 7 or Samsung Galaxy S5. The limitations of such devices are mainly related to the Operating System (OS) since some custom OS versions do not allow the dedicated application to extract the RSSI values at frequencies higher than 25 Hz.

IV. CONCLUDING REMARKS

This paper presented an in-depth study of BLE-based architecture for distance estimation, occupancy detection, and counting. Extended data collection sessions were performed related to the three different scenarios using the Nordic Thingy 52 device as data emitter and daily life Android-based smartphones as the receiver device. Besides, different regression and classification algorithms were tested, achieving optimal results on all scenarios: i.e., between 12 and 9 cm of RMSE and MAE concerning the distance estimation, between 0.5 and 0.3 person of RMSE/MAE about occupancy counting, and 99.82% of accuracy concerning occupancy detection.

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