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Towards a device-free passive presence detection system with Bluetooth Low Energy beacons

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Abstract. In an era of smart information systems and smart buildings, detecting, tracking and identifying the presence of attendants inside of enclosed rooms have evolved to a key challenge in the research area of smart building systems. Therefore, several types of sensing systems were proposed over the past decade to tackle these challenge. Depending on the component's arrangement, a distinction is made between so-called *device-based active* and *device-free passive* sensing systems. Here we focus on the device-free passive concept and introduce a strategy of using Bluetooth Low Energy beacons for device-free presence detection.

1 Introduction

With recent advancements in smart sensor technologies, the transformation of a conventional to a smart building has become a global trend [1]. By expanding traditional technology with intelligent components, smart algorithms and modern infrastructure provide occupants a variety of services like intelligent home entertainment, illumination systems or sustainable use of energy [2]. The quality of these services strongly depends on context-sensitive information about the position and distribution of attendants. Similarly for smart safety systems, the detection of human presence in certain areas of a building is a valuable information in case of hazardous situations. In case of fires, the majority of firefighters may be sent directly into those areas with human presence. Also evacuation scenarios could be optimised using the safest instead of the shortest path.

In order to tackle these challenges, various detection and localisation approaches were proposed, integrating a wide variety of technologies [3]. As WiFi infrastructure is already part of entirely each building, the majority of these approaches is based on the transmission of WiFi signals and their Received Signal Strength (RSS) [4], which, however, is often insufficient due to WiFi signal quality [5]. Therefore, deploying an independent Bluetooth Low Energy (BLE) network with beacon technology for localisation has proven to be an alternative to WiFi technology for indoor sensing systems [6].

According to the arrangement of transmitters and receivers, these systems can be classified into *device-based active* and *device-free passive* sensor systems. Device-based active (dba) sensing systems require target entities to be equipped with a tracking device. Device-free passive (dfp) sensing systems have no need for active participation within the sensing process by the entity, we follow the same line. In this article, we introduce a *device-free human presence detection system* based on BLE. Despite beacons have proven to be an adequate alternative to WiFi, there are only a few systems that use BLE [6] and hardly any systems that combine beacons and dfp sensing [7]. An overview on BLE techniques is provided in Sec. 2. Sec. 3 comprises of some preliminary tests on the suitability of BLE for presence detection. The results of the experiments are presented in Sec. 4 followed by a summary and an outlook on further research.

2 Related Work

The idea of tracking human entities within buildings by using built-in WiFi infrastructure and RSSI observations was first proposed in [8]. Over the following years, many other systems adopted this idea [9] and integrated other radio-frequency types such as Bluetooth, Ultrawideband or ZigBee. These approaches were dba-based only, so nearly all of them had to manage the vast impact of human presence on received signal strength (RSS) [10]. Even the physical attendance of a human body close to the experimental area led to inaccuracies of the signal propagation models. At this time, this phenomenon was perceived exclusively as a handicap for dba sensing that needs to be taken into account whenever designing a dba sensing system.

With the introduction of the *sensorless sensing* concept in [11], effects like multipath fading, shadowing and signal absorption were integrated into the models enabling novel applications such as motion detection, presence detection, people's tracking, and identification. In [12], this idea has been used for the first time to localise humans by dfp-sensing but still using WiFi technology. Overviews of various WiFi-based device-free sensing systems are provided in [13].

Despite the high flexibility and the inexpensive price, there are hardly any combinations of the dfp concept and Bluetooth Low Energy beacons. Best to the author's knowledge, the only combination of BLE and dfp is used in a motion detector for a remote elder care support system [7]. In contrast, the focus of this work is not on the detection of movements, but rather on the general detection of (also immobile) attendees.

Therefore, there is currently no presence detection system that implements BLE in a dfp-system. Such a system prototype is provided in this paper.

3 BLE-based device-free indoor presence detection

Bluetooth Low Energy network refers to a composition of transmitters which are consistently emitting a low energy signal using the Bluetooth protocol. Hereby, the transmitted signal has a lower information content than traditional Bluetooth and may be considered like a ping signal in a computer network without a direct connection between transmitter and receiver. Typically, the receiver gets only a short data frame containing the transmitter's ID, a small information package and a timestamp. This data is enriched by the measured signal intensity, called the Received Signal Strength Indicator (RSSI). Subsequently, such a transmitter is referred to as *beacon*.

In an application scenario, the RSSI is recorded as time series and has to be analysed in further steps. Potential applications could be: people tracking,

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environment monitoring, localisation or presence detection. In the following, our system considers the task of presence detection.

System composition and study design: Dfp sensing systems consist of three components: signal transmitters, signal receivers, and an application for either storing the data or start further data processing [12].

1. *signal transmittance* is accomplished by beacons. The allocation of transmitters is essential to maximise the impact of attendants on RSS. Preferably, the beacons are arranged in such a way that attendants interrupt or disturb the direct signal line between transmitters and receivers.
2. *signal receivers* are accomplished by USB antennas with built-in Texas Instruments CC2540 chips.
3. *storage application*: after signal reception at the receiver, two scenarios are available: either an application stores the incoming data in a database or the packages are directly processed in the context of streaming [14].

Here BLE-based dfp presence detection is applied in an environment of a lecture room as measurement area (120 seats in 8 rows). In order to get a better understanding of the advantages and disadvantages within different transmitter and receiver allocations, ten different test setups were investigated during the test signal recording. As mentioned above, the transmitters should be arranged in such a position that shadowing and absorption are as extensive as possible by attendant human torsos. The best test results occurred in those arrangements with transmitters placed beneath the attendant's seats and the receivers close to the ceiling and laterally to the seating rows. For this purpose, $b = 24$ beacons (3 per row) were located beneath the attendant's seats in order to ensure a high absorption in an occupied and less absorption in an empty room. In our system, we used $r = 4$ receivers. This analysis was based on the visual inspection of the RSSI time series test recordings.

Dataset generation: In order to analyse the impact of the number of attendants with respect to the signal strength of a beacon over a period of time, the progression of RSSI with various occupancies is depicted in Fig. 1. As illustrated in this figure, both the average RSS and the RSS variances increase significantly along with a higher count of attendants.

With a high number of attendants in the measurement area represented by *60 attendants*, the average RSSI of this scenario exhibits a significantly lower value and a substantially higher degree of variance compared to the other two scenarios. In medium occupied rooms (*30 attendants*), the average RSSI is slightly higher and features a smaller variance. The RSSI progression without any attendants (*0 attendants*) occurred almost constant, except in a few cases. In this context, the RSSI mean value and the RSSI fluctuation give some indications whether a room is occupied or empty.

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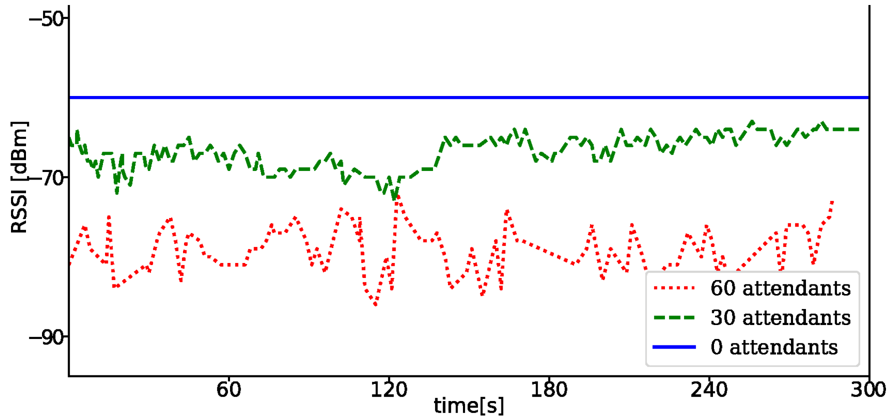

Fig. 1: RSS time series with various room occupancies

To obtain a broad overview of the signal strength behaviour at different degrees of occupancy, about $L = 130$ lectures were recorded, each lecture has a length of 90 minutes. In this time frame, 5 measurements were taken in small slots with a length of $T = 300$ seconds. In total, $N = 130 * 5 = 650$ samples have been recorded, denoted as measurement set X. During the signal recording, the data were labelled as 0 (empty room) or 1(non-empty room). This dataset will later be used in a case study for supervised classification to predict whether a room is empty or occupied. This *raw* data are subsequently denoted by DS1. Here, we make sure that the 5 repeated measurements are not causing any bias in the cross-validation.

Preprocessing: In former work on sensorless sensing [11, 12], preprocessing was widely limited to standard signal processing approaches like filtering or smoothing. This still keeps rather high dimensional datasets, not well-suited for real applications, e.g., in embedded systems. Occasionally, statistical moments have been calculated to summarise the encoded information. Here, we follow this line and calculate 4 features: mean, variance, trimmed mean and trimmed variance on each slot x, where $x_i \in X$, $i = 1 - N$. Trimmed mean and trimmed variance have been calculated using an α-trimmed filter (with $\alpha = 0.05$) following [15], a kind of noise reduction. Hence, we finally get a data matrix of $N \times 4$ features. This data subsequently referred to as DS2. The spatial allocation of transmitters and receivers is not taken into account in [15].

As transmitters differ in distances to the receivers, implementing a weighting factor for each beacon according to its beacon-receiver-distance (brd) is useful when aggregating the whole RSS series to one single value per slot. Therefore, we introduce a normalisation matrix $W \in \mathbb{R}^{b \times r \times 2}$ with $w_{ijk} \in W$. The normalisation terms w_{ijk} are determined as follows: (1) we measure the signal pattern in an empty room with respect to all beacons and receivers. (2) we calculate the minimum and maximum of the respective averaged RSS. (3)

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minimum and maximum are stored as subsequent scaling values for a Min/Max-Normalisation. In the final preprocessing of the real measurements, the slots are normalised using the normalisation matrix W such that the brd are taken into account. In the experiments, we also provide results for data with standard Min/Max-Normalisation ignoring spatial effects in *brd* and results without α-trimming and feature reduction. The normalised DS2 is denoted as DS3

4 Experiments and results

We evaluate our proposed system and preprocessing concept on the aforementioned datasets using logistic regression, nearest neighbor and support vector machines (SVM) [14]. The parameter C of the SVM classifier was identified on an independent training set in a small pre-study with $C = 1$. Parameters of the rbf kernel are auto-optimised in the SVM implementation. The degree of the polynomial kernel is $d = 3$ as commonly used in literature. We used a ten-fold cross validation[1], and the results are reported in Tab. 1.

Classifier	DS1	DS2	DS3
Logistic Regression	0.6981	0.9546	0.9773
Nearest Neighbor	**0.7015**	**0.9690**	0.9872
SVM with lin. Kernel	0.6267	0.9443	0.9819
SVM with poly Kernel	0.6893	0.9545	0.9896
SVM with rbf Kernel	0.6944	0.9646	**0.9897**

Table 1: Comparison of classification models for the data sets: without any preprocessing (DS1), after aggregation and preprocessing (DS2), after normalisation with weight factors (DS3).

With the preprocessing from DS1 to DS2, we were able to reduce the high dimensional RSS series for each beacon-receiver pair to four values. That implies that each transmitter-receiver pair is represented by *mean*, *variance*, *trimmed mean* and *trimmed variance*. The aggregation to those four features results in a successful classification of $\approx 95\%$ shown in Table 1. By weighting the features using a transmitter-receiver-specific factor, we were able to further increase the accuracy of the classifications up to $\approx 98\%$ shown as DS3.

5 Conclusions

In this paper, a system prototype of a dfp presence detection with BLE was presented. For this purpose, an auditorium was equipped with transmitters and receivers and tested. In total, the presence of people was recorded in 130 lectures. By aggregating the measurement series in several stages, we achieved an accuracy of more than 95%. This accuracy was further increased up to 98%

[1]Here we made sure that measurements of the same lecture (repeated measurements) have not caused any bias. Only one of 5 measurements was randomly selected for the training and none of the others in the tests.

by implementing distance-depending weighting factors. Finally, we provided a system in which BLE is well-suited for device-free presence detection.

Future work on this BLE-based dfp system will be twofold: on the one handside, we are interested in simplifying the technical equipment, and on the other hand, entity detection is also extendable to BLE-based dfp human counting. Thus it should not only be possible to determine whether, but also how many people are present which leads to a regression problem. With respect to the subclasses of a sensing system mentioned by [12], the extension from *detection* to *tracking* or *identification* is also an interesting field of research. First tests on counting humans by a BLE-based dfp system are very promising but are subject of further investigation.

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