On the Analysis of Human Posture for Detecting Social Interactions with Wearable Devices

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***Abstract*—Detecting the dynamics of the social interaction represents a difficult task also with the adoption of sensing devices able to collect data with a high-temporal resolution. Under this context, this work focuses on the effect of the body posture for the purpose of detecting a face-to-face interactions between individuals. To this purpose, we describe the NESTORE sensing kit that we used to collect a significant dataset that mimics some common postures of subjects while interacting. Our experimental results distinguish clearly those postures that negatively affect the quality of the signals used for detecting an interactions, from those postures that do not have such a negative impact. We also show the performance of the SID (Social Interaction Detector) algorithm with different settings, and we present its performance in terms of accuracy during the classification of interaction and non-interaction events.**

***Index Terms*—Social Interactions; Proximity; Bluetooth Low Energy**

I. Introduction

Mobile sensing devices offer the possibility of collecting networking information with high temporal resolution. This is the case of Bluetooth Low Energy (BLE) beacons, commonly available on smartphones and wristbands. BLE beacons can be used to estimate the proximity between devices, by analyzing how the Received Signal Strength Indicator (RSSI) varies along the time. Proximity can be used as a valuable proxy for inferring if two subjects are interacting as discussed in [1], [2]. An increasing number of commercial applications rely on the proximity, in order to increase the user experience (i.e., location-based services), but most of the solutions can be affected by the way users *wear* the emitting and the receiving device (e.g., smartphone, wristband, or a tag). In this context, we measure the effect of the human posture on BLE beacons emitted and collected with a wearable device.

People interact in the real-world very differently. As for example, people can stand face-to-face during the whole duration of the interaction, they can interact while walking standing side-to-side, or they can dispose in circle. Furthermore, users can change their posture suddenly in response to an external event. With the term posture we refer to the body orientation of the subjects involved, such as face-to-face, side-to-side or a combination of them. The variety of such postures is quite extended and it is not the intention of this work to cover all the possible combinations. Our goal is rather to focus on some common postures that subjects assume during an interaction, with the goal of measuring how the beacon's signal strength is affected by such postures.

In particular, we report our experience with the NESTORE[1] sensing kit, specifically designed to collect and advertise BLE beacons. The wristband listens and stores BLE beacons, while BLE tags emit beacons. This work firstly describes a data collection campaign that we carried out in our working place. The dataset has been collected during three working days, during which we reproduced interactions by varying how the body position of the users. The dataset also provides a pure-calibration session during which subjects wearing the tag assumed 16 different postures. The analysis of this dataset shows that some postures increase the signal strength of beacons collected, as for example postures in which emitter and receiver are on the same line of sight. We also found some disrupting postures that reduce the quality of BLE beacons recorded by the wristband. The results of our analysis with the calibration session highlight the importance of considering also the posture for the purpose of detecting proximity between users. This work also presents the performance assessment of the Social Interaction Detection (SID) algorithm. SID is a cloud-based service, designed to periodically fetch and analyze beacons collected with the NESTORE sensing kit. Data are elaborated by extracting some statistical features of the beacons collected. As a result, SID returns a time series of social events (i.e., start and end of the interaction for every dyad) as well as a summary of some useful metrics of the interactions detected. The rest of the paper is structured as follows. Section II surveys recent advances from the literature addressing the identification of social interactions with wearable devices. Section III describes the experimental settings, we describe the NESTORE kit and the dataset we collected. Section IV analyzes how the posture affects the RSSI of BLE beacons collected. Finally, Section V introduces the SID algorithms and its performance in terms of accuracy.

II. Related Work

Automatic proximity detection is usually based on wearable technologies, mostly as custom hardware (e.g., the SocioPatterns[2] platform [3], [4], based on RFID emitters/receivers, the Sociometric Badge [5], [6], based on RFID and voice detectors, and the Rhythm badge [7], based on custom Bluetooth).

[1]https://nestore-coach.eu/
[2]http://www.sociopatterns.org/

This kind of approach relies on a custom hardware design which makes it difficult to think to a large-scale experiment. Furthermore, both of the badges are based on the RFID technology not always available on commercial smart phones or wearable smart devices. A different approach is described in [8] that uses a custom wristband based on standard BLE beacons to detect social interactions. This approach is in line with the architectural approached used in our work and it represents a step forward an easy integration in available off-the-shelf devices [9], [10]. It is worth to notice another interesting project named the Copenhagen Networks Study [11]. Such study involved approximately 800 students from University of Denmark for a period of two years. The study aims to collect different kind of data through a mobile app. Among the data collected, also the proximity among students is detected by exploiting Bluetooth periodic scans and WiFi signals as reported in [12]. Such work increases the dimension of the experiments with a large dataset collected over the years. Another interesting dataset collection is provided by [13], with a fine-grained location estimates as ground truth and different socialization scenarios.

Traditionally, the study of the effect of human body on the signal propagation in the 2.4 GHz band is a trend topic in the networking research area [14], [15]. This is still valid for the BLE technology [16]–[18], but a study on the effects on proximity and, in particular, in the social interaction detection scenario is, to our knowledge, still missing.

III. Experimental Settings

Data analyzed in this work are obtained by adopting the NESTORE sensing kit. Such kit is the result of the design and implementation phase carried out in the context of the NESTORE EU project. Section III-A describes the hardware we used, while Section III-B describes the resulting dataset.

A. The NESTORE sensing kit

The NESTORE sensing kit is composed by a wearable device equipped with various kind of sensors, and two different kind of BLE tags, as shown in Figure 1. The NESTORE wearable device is a custom wristband specifically designed for the purpose of this project. The device is powered by a lithium battery with a wireless charging system and it embeds a 32-bit MCU with BLE interface and various sensors like a Heart rate PPG sensor, a 3-axis accelerometer and a barometric altimeter. Thanks to the sensors set, the NESTORE wristband can monitor constantly various user's parameters like instantaneous heart rate, steps count, climbed steps, calories and then store all these information inside the on-board flash memory. The heart rate parameters are detected using a high-performance PPG sensor that, thanks to the embedded algorithms, can precisely evaluate the kind of activity, burnt calories and various information like HR zone, HR recovery, resting HR, step rate and count, Vo2. Besides this, the device periodically scans for the presence of nearby beacons and, in case of positive detection, it stores all the gathered information inside the flash memory. All the beacons MAC addresses are also stored inside the device memory, so that the beacons detected can be precisely identified. Table I reports the hardware features of the NESTORE wristband.

TABLE I: Hardware features of the NESTORE wristband.

Hardware features	
Core	32-bit Ultra Low Power MCU, with BLE interface
Non-volatile memory	512 Mbit, NOR Flash memory
Heart rate sensor	Valencell Benchmark Wrist, 1.2 PPG sensor
Accelerometer	Low Power 3-Axis 2g to 8g, MEMS Accelerometer
Barometer	MEMS Digital Pressure Sensor, 300 to 1100 hPA
Display	0,96" TFT LCD with,80x160 dot resolution
Battery	95 mAh rechargeable polymer,lithium battery

There are two kind of NESTORE BLE tags: environmental and social. The first are designed to be deployed in different locations (e.g. the fridge door, the entrance door, living room or meeting office). Every environmental tag is equipped with a 3-axis accelerometer used to detect any movement of the object to which the beacon is attached (i.e door opened). Moreover, tags periodically monitor temperature and humidity by exploiting the on-board digital sensor. All the sensor information and the battery level are periodically advertised through the BLE interface.

Social tags are designed to detect interactions between people. They can be locked on the key-chain. This kind of tags are not equipped with any environmental sensor, rather they periodically advertise BLE beacons as well as the battery level through the BLE interface.

Fig. 1: The NESTORE wristband and BLE beacons.

The beacon advertising and the beacon scan are two operations with a high power consumption of the tag and the wristband, respectively. In order to reduce the battery consumption, both of the operations have to be optimized. In particular, the scan period should be kept as short as possible, but at the same time, enough to guarantee to collect enough beacons for the analysis. Similarly, the beacons advertising should also be reduced. An acceptable compromise of the duration of the two operations is given by the following configuration:

- Wristband: scan duration 758 milliseconds, scan period 3 seconds;
- Beacons: advertising interval 350 milliseconds.

Therefore, every 3 seconds the wristband performs a beacon scan of duration 758 milliseconds. While, tags advertise beacon every 350 milliseconds. With such a setting, our preliminary results show a balance between battery consumption and an acceptable reduction of the beacon loss. More specifically, we performed several runs of wristband's scan period with the goal of minimizing the battery consumption and maximizing the amount of beacons collected. We report in Figure 2 the life-cycle of the advertisement and scan operations (both environmental and social tags).

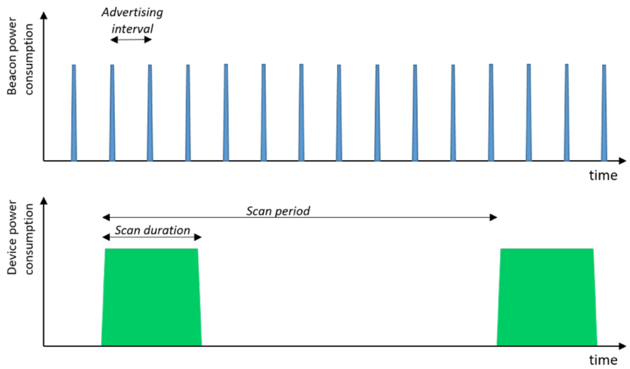


Fig. 2: The life-cycle for emission and reception of BLE beacons.

B. The Experimental Dataset

The dataset we collect comprises a *calibration* session and two *interaction sessions*.

The goal of the calibration session is to collect BLE beacons by varying the posture of the users involved. More specifically, the first user stands in the same posture during all the calibration session, while the second user assumes different postures: 4 positions: North (N), East (E), South (S), West (W) and 4 orientations: 0°, 90°, 180°, 270°, as reported in Figure 3. As a result, we tested 16 different postures that, in our opinion, cover the majority of the layouts commonly adopted when users interact in the real-world. Users stand on the same posture for 4 minutes, as a result we collected a total of 64 minutes of monitoring. The blue user in Figure 3 stands with the same posture for the whole duration of the calibration session, while the user depicted in black moves according to the different postures. Every row of Figure 3 reports the 4 positions, while columns report the 4 orientation. During the calibration session, users stand 1 meter distance, so that to mimic a volunteer interaction. Both of them wear the wristband and one social tag. The user depicted in blue wears the wristband of the left arm, while the user depicted in black on the right arm. Both of them also wear a social tag locked on their key-chain located front-side.

Differently, the interaction sessions reproduce a sequence of face-to-face interactions between a pair of subjects. Such sessions comprise a set of tests, and each test is designed to mimic three common stages of a social interaction: Non interaction, Approaching and Interaction as reported in Figure 4. More specifically, during the Non Interaction and Approaching stages we assume that subjects do not interact, while only

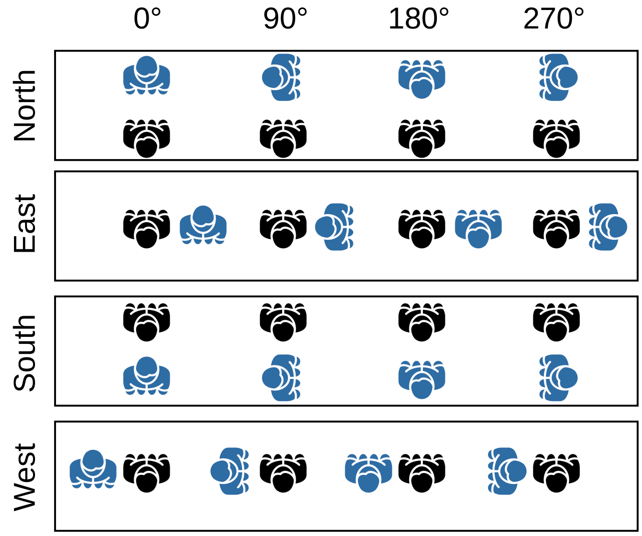


Fig. 3: Layouts of the calibration session.

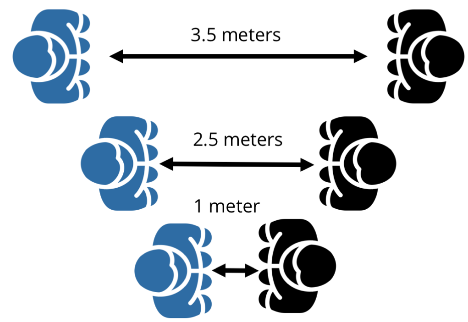


Fig. 4: Stages of a social interaction.

during the Interaction stage subjects are considered interacting. Each test follows this protocol:

- Non Interactions: subjects stand at 3.5 meters distance face-to-face for 1 minute;
- Approaching: subjects move at 2.5 meters distance face-to-face for 1 minute;
- Interaction: subjects stand at 1 meter distance face-to-face for 4 minutes;
- Approaching: subjects move back at 2.5 meters distance face-to-face for 1 minute;
- Non Interactions: subjects move back at 3.5 meters distance face-to-face for 1 minute.

As a result, each test lasts for 8 minutes of which 4 minutes of absence of interaction (stages: Non Interaction and Approaching) and 4 minutes of Interaction. Each session is repeated for 5 tests. Tags are positioned differently for the two sessions:

- Session 1: tags locked on the key-chain front-side;
- Session 2: tags put on the back pocket.

Finally, we also tracked the ground-truth of the interaction sessions, corresponding to the time periods during which the 2 users were actually interacting face-to-face. The ground-truth is obtained by annotating the timstamp of the start and end time of the social interaction.

IV. Evaluation of the Signal Strength with Different Postures

The calibration session has the goal of analyzing how the different postures, commonly assumed during a real-world interaction, influence the quality of the collected data. In particular, we focus on the effect of the body on the attenuation of the RSSI of received BLE beacons. Figure 5 shows the mean of RSSI values collected at the four positions (S, E, N, W) and at the four orientations (0°, 90°, 180°, 270°) of the moving user (depicted in blue), with respect to the standing user (depicted in back). The four points on each grid represent the mean values of RSSI collected by the receivers of both the moving and standing user. The red dots represent the position of the device on the user. As can be seen from the figure, the RSSI drops from a max value of -65 dBm (as average over the 4 minutes of data collection per each posture) to -80 dBm, in the best configuration (receivers facing the emitters) and worst configuration (bodies back to back), respectively. It should be noted that the calibration session has been carried out at 1 m distance between the two users, but nevertheless the inherent characteristics of the BLE signal's propagation (i.e., multipath fading) strongly affects the quality of the signal in terms of overall power, especially in the reference scenario configuration (i.e., low power transmitting and receiving antennas in order to optimize energy). Besides the effects of the cluttered environment in which the dataset has been collected, Figure 5 confirms a clear attenuation effect of the human body when interrupting the line of sight of the devices, like in the combinations (position, orientation): (W, 0°) and (S, 0°) in Figure 5a, (E, 90°) in Figure 5b, (N, 180°) and (E, 180°) in Figure 5c. Furthermore, we can observe that also the position of the device influences the signal strength of the BLE beacons: it is explanatory the case of orientation 270°in Figure 5d in which we can see how, even when the moving user faces the standing user, the RSSI fluctuation remains similar, with low values, in all the positions.

V. Detecting Social Interactions

We now analyze the effect of different user's postures for the purpose of automatically recognize a social interaction. To this purpose, we first describe the SID algorithm that we used for this analysis (see Section V-A) and then we study how tags positioned differently can affect the performance of SID (See Section V-B).

A. The SID Algorithm

SID has been designed and developed in the context of the NESTORE [19] project. SID has been implemented by exploiting the experience gained with the SME-D algorithm, originally presented in [20], but with a complete different architecture, design and hardware adopted. SID performs two core operations:

- to fetch BLE Beacons from the backend;
- to analyze the data collected and to recognize the interactions.

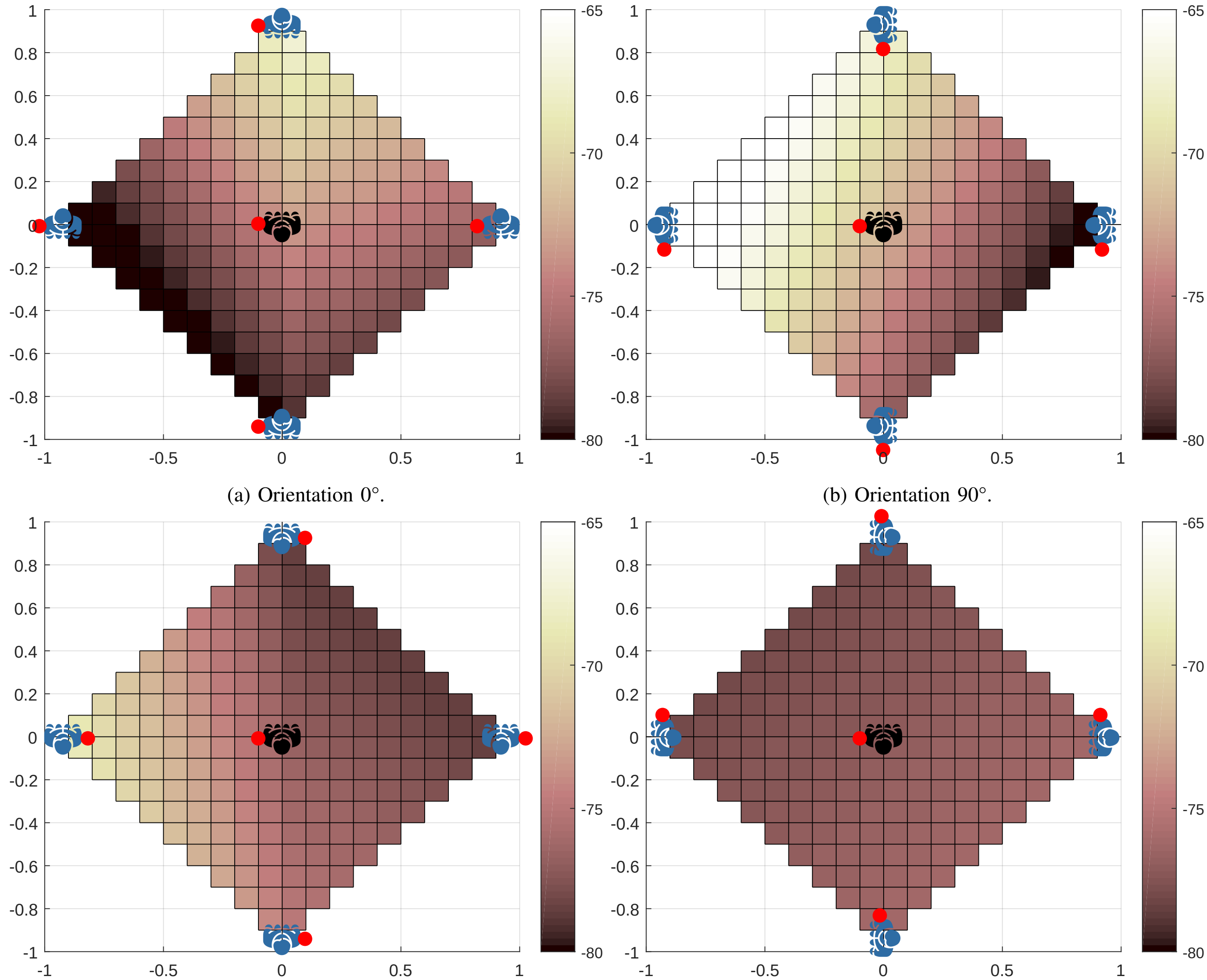
SID can fetch data by using different data providers. We implemented three providers: CSV, MongoDB, and the NESTORE provider. All of them are supposed to provide a sequence of beacon readings with the following format: timestamp, identifier of the receiving device, identifier of the emitting device and RSSI in dBm. SID is implemented as a Cloud-based service. It is deployed on a virtual machine and it periodically performs the two operation previously described. SID provides a set of Java Management Extension (JMX) interfaces in order to control remotely its behaviour.

SID analyses the beacons' readings in order to detect when two subjects are co-located. e.g. they are close to each other at the same time. In turn, the co-location is used to infer the existence or the absence of an interaction event as analyzed in [1]. SID firstly starts a profiling operation, during which the algorithms retrieves the list of users wearing a wristband and the tags. Such information are used in order to retrieve from the NESTORE provider all the beacon readings from each of the users. Then, SID analyzes for each user the data its device provides. More specifically, SID analyzes two properties of the beacons collected from the NESTORE wristbands, namely the loss rate and the RSSI of the beacons received. The beacon loss rate allows SID to consider chucks of data with at least the $p\%$ of the expected beacons. While the second properties checks for some statistics about the RSSI of the beacons received, in particular we consider the mean value that is expected to exceed ρ dBm. If the two properties hold, then SID logs an interaction, by reporting the following information: $[timestamp, user, partner, start/endinteraction]$. SID checks that the interactions is *preserved* along the time up to its end.

B. Effects of Posture on the SID Algorithm

We now further investigate the effect of the position of the Bluetooth tag presented in Section IV. To this purpose, we execute the SID algorithm with the 2 interaction sessions described in Section III-B. Our goal is to show those differences emerging from 2 positions of the Bluetooth tags: front and back pocket. More specifically, the sessions reproduce a sequence of interactions between two users in an indoor environment. During the first session, users place the tags on the front pocket while on the latter case, users wear the tag on their back pocket. We analyze the performance of SID, by comparing the ground truth of the interaction sessions with respect to the results provided by SID.

We measure the performance of SID by varying the beacon loss rate $p\%$ and the threshold ρ. More specifically, we vary $p\%$ with steps of 20 points, ranging from 10% to 90%, and we vary ρ with steps of 2 dBm from -90 dBm to -60 dBm. For each of the previous configurations, we compute the Accuracy metric of SID. Figure 6a shows the results of SID with the first session, while Figure 6b shows the results with the second session. Each of the figures, shows the results from the 2 users separately. Results from session 1 are plotted with values of ρ ranging from -73 to -62 dBm since the Accuracy outside such ranges is meaningless. In this case, the maximum Accuracy is



(a) Orientation 0°.

(b) Orientation 90°.

(c) Orientation 180°.

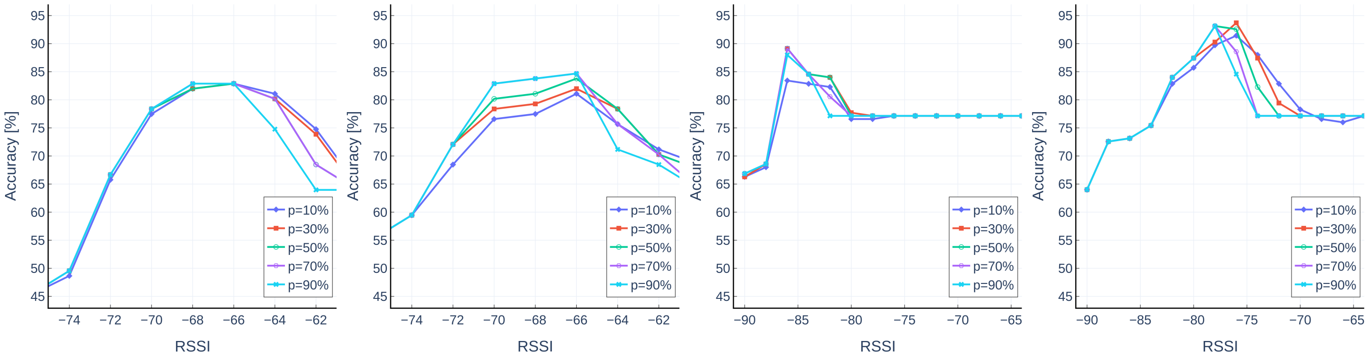
(d) Orientation 270°.

Fig. 5: Postures of users at different positions (N,E,S,W) and different orientations (0°, 90°, 180°, 270°). The red dot represents the position of the receiving device on the user.

of 85% and it is obtained with $\rho = -66$ dBm and $p = 90\%$ (for both of the users). Differently, results from session 2 show a very different behaviour with the two users. We plot the Accuracy in a wider range with respect to session 1, ranging from -90 dBm to -65 dBm. In this range, the Accuracy varies more widely, the optimal Accuracy is obtained with different values of ρ and p for the two users (user 1: $\rho = -85$ dBm, and $p = 70\%$, user 2: $\rho = -75$dBm and $p = 30$ %), but in both of cases ρ and p remarkably differ from the optimal ones found with scenario 1. In particular, we observe that the maximum Accuracy in scenario 2 is obtained with $\rho = -66$ dBm and $p = 90\%$ is 75%, about 10% lower than that of scenario 1. We consider that such differences are mainly caused by the attenuation of the RSSI due to the position of the tag.

VI. Conclusions and Ongoing Works

Detecting social interactions at realistic conditions is challenging. A promising approach, consists in inferring the existence of social interactions between subjects, by detecting their proximity. This approach can be implemented by exploiting short-range network interfaces such as Bluetooth Low Energy. Under this context, BLE beacons are a cheap, commercial and energy-saving solution. We study in this work the effect on the signal strength of beacons collected with the NESTORE sensing kit. We first describe our experimental dataset and then we show how 16 different postures affect the quality of the BLE beacons recorded with the NESTORE wristband. As a further analysis, we show the impact of two typical scenarios to the performance of the SID algorithm designed to detect



(a) Accuracy of SID for user 1 and 2 with tags in front pocket. (b) Accuracy of SID for user 1 and 2 with tags in back pocket.

Fig. 6: Accuracy of the SID algorithm varying the position of the BLE tag on the user: front and back pocket.

automatically social interactions. We show how the Accuracy varies when the emitting device is positioned on the front and on the back pockets, and we show how the optimal setting for a scenario does not fit with respect to the second one. The analysis done along this work, gives rise to further lines of investigation. On the one hand, we are interested in understanding automatically the user's posture, at least being able to distinguish between standing user, walking user or sitting user. Such contextual information can be exploited by SID in order to adapt its settings to the current situation. Moreover, we are also interested in combining learning mechanisms in order to self-calibrate SID, so that to avoid to select an optimal setting, rather to let SID decides the best configuration that minimizes false positive and false negative answers.

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