RSSI Based Passive Detection of Persons for Waiting Lines Using Bluetooth Low Energy

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Abstract

Knowledge about the presence of persons in a waiting line can help estimating the waiting time or guiding the decision about opening a second line. However, existing presence detection systems for waiting lines are either mounted at fixed positions, take a long time to deploy, need a power connection or require users to carry devices. Past research on the analysis of the Received Signal Strength Indicator (RSSI) of a radio transmission indicates that it can be used to detect the presence of persons. Here, the accuracy of the detection is directly linked to the quality of the radio link. Radio links based on Bluetooth Low Energy (BLE) offer a stable connection, but implement a mandatory frequency hopping scheme, with the information about the current channel typically not accessible. In this work we extend the concept of passive presence detection to work on BLE radio links. We adapt two RSSI based presence detection techniques and evaluate their performance in experiments. The experimental results indicate that it is possible to achieve a 92% accuracy using BLE when compared to the ground truth.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Passive presence detection, human queue monitoring

Keywords

Wireless, RSSI, BLE, waiting lines

1 Introduction

Waiting lines occur in everyday urban life, for example at airports, supermarkets, amusement parks or coffee shops. A waiting line consists of a service point where the available resource, e.g. a cup of coffee, is distributed, and a queueing area. If the time it takes to distribute a resource, i.e. the service time, is greater than the time between arrivals of new persons in the system, i.e. the interarrival time, people will queue before the service point. Queueing areas are often controlled by portable barrier poles connected by retractable belts. Frequently, the layout of these barrier-systems needs to be changed by moving the poles to a different position and reconnecting them. For example in an airport rearranging the waiting line might be necessary to guide passengers to a different check-in counter. While more people are arriving, knowledge about the presence of persons in the waiting line enables smarter decision making regarding the opening of new service points or secondary lines to balance the load. However, current systems estimating the attributes of waiting lines are often installed at fixed positions and can not be changed in their layout. Other systems require time-consuming calibration after each layout change, which reduces their applicability. Thus a mobile queueing system which is easy to deploy and supports arbitrary sensor positioning is required.

In recent years the Received Signal Strength Indicator (RSSI) of radio transmissions has been analysed for its potential to detect persons in indoor environments [9]. If a person steps into the monitored area, i.e. the area covered by a radio link [11], the human body will cause *multipath fading* of the radio signals [21, 18]. Depending on the path the signals take, they can arrive at the receiver with lower or even higher power. This interference is perceivable as a variation in the received signal strength when comparing the values of consecutive messages. To study the disturbances in the monitored area, techniques based on e.g. recording and analysing the mean RSSI or the RSSI variance have been introduced [9, 18, 10, 1]. Algorithms based on these techniques have been shown to detect the presence of persons with positioning errors of only a few centimetres. These algorithms can also be used as a basis to estimate the attributes of waiting lines [14]. Battery powered radio transceivers could be deployed atop freely movable barrier poles which allows for a flexible layout that is easy to change.

The challenges in designing a reliable detection algorithm for such a system lie in the naturally fluctuating behaviour of the RSSI. Variations in the signal strength caused by the en-

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vironment have to be differentiated from disturbances due to human presence. For this reason, the presence of a person in a more stable radio link is easier to identify than in a link that is heavily fluctuating. Compared to radio links using other wireless technologies, BLE radio links demonstrate greater stability [5, 7]. This quality has the potential to benefit the accuracy of presence detection algorithms immensely.

However, BLE transmissions are sent on multiple channels, each of which has it's own RSSI level [6]. If the channels are not handled independently, channel switches can cause changes in the RSSI that will influence the detection performance of the algorithms. Furthermore, BLE implements a channel hopping scheme in which the information about the current channel is typically not accessible to application programmers.

Our goal is the creation of a mobile barrier-system capable of detecting persons passing through it. The desired characteristics of this system are portability, a simple deploying procedure and a high detection accuracy. Our contributions extend the concept of passive presence detection to BLE radio links and adapt existing techniques to cope with the different BLE channels. Further, we design a prototype mobile queueing system that can be used to estimate the presence of persons in waiting lines. The prototype system is easy to deploy, does not require additional infrastructure and supports arbitrary sensor positions. We validate its performance in experiments to demonstrate the extended algorithm's abilities to be used as a basis for a freely deployable presence detection system.

Apart from waiting lines the availably of such a system would also enable different kind of application scenarios. A mobile presence detection system could monitor congestions at emergency exits guiding people to alternative escape routes, or register trespassing at security sensitive locations.

This paper is structured as follows: First, we take a look at the related work in the fields of passive presence detection, BLE and queueing systems in Section 2. Then, we describe the advantages and challenges of the BLE protocol in Section 3. Section 4 presents our approach to create robust detection algorithms based on BLE, while Section 5 evaluates their detection performance in experiments. We conclude with a summary of our results and a brief look into our future work.

2 Related Work

In this section related works on presence detection and queueing systems are discussed.

The detection of a person in the area covered by a radio link is a well-established research topic in recent literature, featuring various techniques. Each technique focuses on analysing one or more measurable attributes of a radio transmission, like the Time of Flight, the mean of the RSSI or the variance of the RSSI.

For example, in [1] the Time of Flight of radio messages is analysed using an array of five antenna pairs simultaneously transmitting and receiving. When the signal is reflected from a physical object, like a human body, the distance of the person can be estimated as an ellipsis around the antenna device. By overlapping five ellipses, one for each antenna pair, the position of up to five people in a room can be approximated.

Alternatively, the RSSI of a radio transmission can be used for detection purposes. In [4] these techniques are coarsely divided into two classes based on either the mean RSSI or the RSSI variance. An early work based on the mean RSSI is [9], in which a correlation between the RSSI of a radio link and a person obstructing it is established. If the current RSSI is attenuated by one standard deviation below the mean RSSI a detection event can be assumed. In [18, 11] the RSSI is used to visualise the presence of a person in a radio network. This procedure, called Radio Tomographic Imaging (RTI), allows to create an attenuation map of the monitored environment. Nodes are deployed on the edges of the monitored area, building a dense grid of radio links. Disturbances introduced by the attenuation of the human body can be detected and the position of the disturbance is pin pointed by overlapping the affected links. Techniques based on the variance of the RSSI can be found in for example [19] and [10]. In [19], building on the RTI system of [18], the RSSI variance in the monitored area caused by human motion is analysed. The introduced VRTI system is shown to detect and track the movement of persons in realtime. In [10] the results of the previous works are extended to cope with the fluctuating behaviour of the RSSI. A long-term variance, only updated in tranquil phases, and a frequently updated short-term variance, which is heavily influenced by the presence of a person, are computed and afterwards compared. If the difference between the two is above a detection threshold, an event is triggered. While variance based systems limit the influence of changes in the RSSI over time, they also require variance inducing movement of the persons in the monitored area. In waiting lines, where motionless standing is an integral part of the process, this is not necessarily the case.

All the works above are heavily based on the quality of the RSSI. A stable connection can improve the detection accuracy significantly compared to a connection with a very fluctuating RSSI. Addressing this issue, in [20] radio links are separated based on their quality and behaviour into *anti-fading* and *deep-fading* links. Anti-fading links will experience an attenuation in the RSSI values when a person enters the link, due to the dampening of the radio signal by the human body. If a person enters the area affected by a deep-fading link, the RSSI of the link may even rise. This can happen because the signal distortion caused by the human body can amplify the otherwise weak RSSI by creating new paths for the radio waves, thus allowing for an increase in the measured signal strength.

Most of the techniques mentioned above are using radio technology based on the IEEE 802.15.4 standard. While many discoveries applying to protocols based on this standard, e.g. the existence of anti-fading and deep-fading links, also apply to BLE radio links, additional challenges have to be addressed. The quality of BLE radio links is analysed in [6]. It is shown, that all three BLE advertising channels can have distinct mean RSSI values. The work also describes the influence of *fast fading* effects on the RSSI of the BLE protocol. A conveyor belt is used to uniformly measure the RSSI at different distances. It is observed that even slight changes in the position can influence the RSSI of a BLE radio link greatly. In [7] this topic is expanded by further analysing the effects of the different advertising channels. It is discovered that the advertising channels exhibit fading at different spatial positions. In [22] BLE is used for fingerprinting, a state of the art scheme for indoor positioning. Here, the advertising channels are handled independently, which avoids "smearing"[6] the RSSI over all channels and greatly improves the localisation performance of the presented algorithm.

Looking at queueing systems, current techniques estimating the presence of persons in a waiting line can be classified into participatory systems, requiring user participation, or autonomous systems, which do not. Participatory systems require users to carry devices, e.g. a smartphone with a specialised, traffic generating app installed [13, 17]. They are making either use of one of the smartphones sensors, e.g. the accelerometer [13], or the smartphones wireless capabilities [17, 12, 16]. In this way, the accelerometer data of a smartphone transmitted to a server can be used to identify periods of moving, i.e. "shuffling forward" or waiting [13]. Alternatively, the RSSI of a smartphones WIFI can be used to estimate the users distance to the service point. In [17] a single signal monitor at the resource service point of the waiting line is recording whether a WIFI signal grows stronger or weaker. If the signal grows stronger, a person is approaching the signal monitor, i.e. entering the line. If the signal gets weaker quickly, the person is leaving the waiting line. In both cases the number of connections can help to estimate the number of people in the line. The above-mentioned techniques require at least some users to carry additional hardware, namely in the form of smartphones, to generate detectable traffic. While smartphones are largely common in urban areas with ownership rates nearing one hundred percent [12], the issue these systems face is the users incentive to participate [15]. Otherwise, not enough sensor data for the analysis will be generated.

Autonomous systems employ sensors at fixed positions to monitor the area of the waiting line, instead. Current technologies are generally based on cameras or beam-type sensors, like laser-beam, light-beam or infra-red systems. Camera based systems analyse the pictures or videos taken for human presence by executing for example face recognition algorithms. However, cameras only have a limited field of view which requires adjustments when the monitored area changes. They also raise privacy issues, since everybody in the system could be identified. Beam-type sensor based systems use laser or light beams received by a light sensor. If the beam is interrupted, for instance by a person crossing it, the system triggers a detection event. However, the beams must be adjusted precisely to hit the receiving light sensor, a process not robust to position changes, and the light sensor must be shielded from direct sunlight to avoid detection failures. An example for an autonomous radio based queueing system is [14]. Here, the quality of radio links disturbed by vehicles is analysed to estimate road occupancy and traffic queue lengths.

The approach we are suggesting is RSSI based passive presence detection of persons which does not require user participation and that is not limited to absolutely fixed sensor positions.

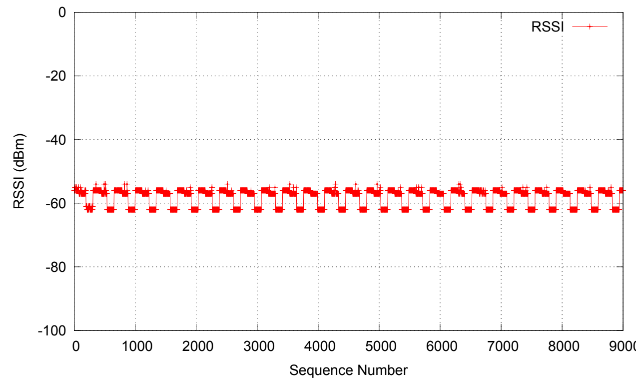


Figure 1. First 15 minutes of the 18-hour measurement to observe the long-term behaviour of a BLE radio link.

3 Challenges in using BLE for Presence Detection

Traditionally, most works in the area of passive presence detection consider techniques based on the IEEE 802.15.4 specification for wireless communication or WLAN [9]. However, with the rising popularity of smartphones new specifications have been introduced. A protocol based on such a specification is Bluetooth Low Energy (BLE) [2]. The BLE protocol was designed to replace the wiring between a central device, e.g. a smartphone, and peripheral devices, e.g. radio beacons. The design goals of BLE are to offer the capabilities of wireless, short-range data transmission with low energy costs [2]. BLE uses 40 channels in the spectrum between 2402 MHz and 2480 MHz, each channel separated by 2MHz. In comparison WLAN 802.11g/n uses only three channels in the same spectrum, but each is 16.25MHz wide. IEEE 802.15.4 uses 14 channels, each 5MHz wide. The three BLE channels 37, 38 and 39, evenly distributed over the spectrum, are used as primary advertising channels as specified in Bluetooth 4.2 [2]. Here, advertising messages are broadcasted, typically by a peripheral. When a central device receives an advertising message, it can initiate a BLE connection. Information can be transmitted between connected devices on the remaining 37 data channels, either from peripheral to central or vice versa. Since the introduction of Bluetooth 5.0 it is also possible to re-purpose data channels as secondary advertising channels. However, to avoid conflicts with older Bluetooth versions, only the three primary advertising channels are used by default [3].

Passive RSSI based presence detection requires multiple consecutive messages being sent whose RSSI values can be compared to identify the disturbances indicating a person. Using BLE, these messages can be broadcasted on the advertising channels avoiding the time-consuming establishment of an actual BLE connection. For the design of a presence detection algorithm on top of BLE it is important to recall that the different BLE channels can have their mean RSSI at different levels [7]. Because of this, computations for each channel have to be handled independently [22]. Otherwise, the different levels would cause sudden jumps in the RSSI, which could in turn lead to false positives. This would occur if the BLE channels are switched, and the RSSI is "smeared" over all channels. Because of this, the RSSI variance computed using all advertising channel of a BLE radio link is high. In turn, the RSSI of each single BLE channel is very stable. Figure 1 shows a section of an experiment recording the RSSI of the three BLE advertising channels over a duration of 18 hours. Two radio nodes have been set up in a laboratory environment at a distance of 1m. The results show that, while all advertising channels have a different mean RSSI level, the standard deviation around each mean on the undisturbed channels is very low. In our experiment 217737 samples have been sent in total, which corresponds to 72579 messages per channel. The measured mean RSSI on each channel was at −56.607dBm for channel 37, −57.426dBm for channel 38 and −61.999dBm for channel 39, with respective standard deviations of 0.312dBm, 0.486dBm and 0.017dBm. In comparison, the recorded standard deviation in [5] of 33000 WiFi samples is at 4,72dBm. This behaviour of the RSSI is promising when trying to analyse the disturbances in a BLE radio link to detect the presence of a person. Fluctuations in a link less likely to be affected by the environment could be a stronger indicator for human presence.

Switching the advertising channel is part of a mandatory frequency hopping scheme BLE implements due to which the advertising channels are changed in short intervals. Channel information are only available with special hardware or not at all. For example, [6] proposes the use of a device with the operating system iOS7 installed, which allows the API to access the channel information of the message. However, often the BLE radio stack is a closed system with no configuration possibilities, in which the information about the advertising channel of the current message is hidden from the application programmer.

Furthermore, radio signals transmitted over the narrowband BLE channels are more highly influenced by fading effects [6] than e.g. signals transmitted over WLAN. The high susceptibility of a BLE towards fast fading excludes presence detection scenarios, in which a constant movement of the radio nodes is required, e.g. mounted on a robot or drone. Also, BLE radio links are still experiencing the same anti-fading and deep-fading behaviour as described for IEEE 802.15.4 radio links in [20]. Possible detection algorithms have to account for these issues.

4 Approach

In this section, we describe how to use passive detection based on the RSSI values of a BLE radio link in order to detect the presence of persons in a waiting line. Passive RSSI based detection allows to build systems which are flexible to deploy, have a low set-up time and for which users do not have to carry any device. Radio signals are transmitted omnidirectional and can even pass through certain obstacles, e.g. furniture or walls. There is no restriction to a field of view, like in camera based systems, and no privacy issues, since the identity of a person passing a radio link cannot be inferred. Furthermore, the transmitter and receiver forming a radio link can be freely deployed preferably on the edges of the monitored area. They are not limited to fixed positions and do not need to be wall-mounted avoiding time-consuming calibration of laser-beams. RSSI based detection can be classified in techniques focused on the RSSI variance or focused on the mean RSSI [4]. Variance and mean are computed by analysing the changes in the RSSI of consecutive messages send on the same radio link. A detection event is triggered by these techniques when a person is assumed to be in the radio link.

To determine which technique is better suited for the presence detection we extend one RSSI variance and one RSSI mean based algorithm to work on BLE radio links and compare their behaviour in the evaluation section.

4.1 RSSI Variance Based Technique

Detection algorithms based on the variance of the received RSSI values are best suited to detect motion in a monitored area since they analyse disturbances of the RSSI. These disturbances are caused by the human body influencing the radio signals in a monitored area when a person enters the radio link. The variance of a sample set of RSSI values is computed as seen in Equation 1,

$$Var(x) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2 \tag{1}$$

for which in this case x_i is the received RSSI value, μ is the mean over all received RSSI values, i.e. the mean of the sample set, and n is the number of all received RSSI values, i.e. the magnitude of the sample set. During the runtime of a detection system the complete sample set of all RSSI values is not previously known. In order to use Equation 1 as a basis for the variance based algorithm, we additionally introduce a sliding window to our approach. Using a sliding window with a window-size of var_{window}, only the var_{window} newest values are considered for the variance computation. By doing so we create a trade-off between the responsiveness of the system and the accuracy of the variance computation. If the sliding window is too large, the system will respond with a delay to a reduced variance in the RSSI since old values are still used in the computation. This can lead to a delayed detection of a person entering or leaving the radio link. If the sliding window contains too few samples, each new sample will have a significant impact on the computed variance introducing unsteady behaviour. This would lower the overall accuracy of the computed value when used in the presence detection. To determine the value for var_{window}, we analyse the time it takes a person to cross the monitored area. Depending on the walking speed and the body type we observe a duration between 300 and 500ms. This equals three to five samples at a message rate of 10 messages per second. For this reason, we set the sliding window size var_{window} to include $var_{window} = 10$ RSSI samples in our experiments, doubling the worst-case value. This way, we can accurately detect changes in the variance while still keeping a high responsiveness. In order to compute the sliding variance, we first create a sliding window with var_{window} slots for each BLE channel. Then, we compute a weighted mean applying Equation 2.

for $i \in \{37, 38, 39\}$ **do**
  if $Channel = i$ **then**
    $Mean^i_{current} = \text{Eq. } 2(Mean^i_{old}, RSSI^i_{current})$
    $Mean^i_{old} = Mean^i_{current}$

    $slidingWindow^i.add(RSSI^i_{current} - Mean^i_{current})$
    $slidingWindow^i.remove(oldestentry)$

    $Variance^i = \text{Eq. } 1(slidingWindow^i)$
    if $Variance^i > T_v$ **then**
      $detectionState = 1$
    else
      $detectionState = 0$
    end if
  end if
end for
return $detectionState$

Figure 2. RSSI variance based detection algorithm.

The weight factor α is set to $\alpha = 0.9$ so that the last received RSSI value has an influence of 10% on the weighted mean.

$$Mean_{current} = \alpha * Mean_{old} + (1 - \alpha) * RSSI_{current} \quad (2)$$

The $Mean_{old}$ in Equation 2 is not based on a sliding window, but a weighted sum of all previous RSSI values. When a new RSSI value $RSSI_{current}$ is received, the difference of the new value to the weighted mean is added to the sliding window for each channel respectively. After the sliding window has been updated, all elements in the window for the current channel are added and divided by the number of elements following Equation 1 to compute the variance. Then, the new RSSI value is used to update the weighted mean. When the variance crosses a threshold T_v a detection event is triggered. This threshold should be set to a value greater than zero to account for small deviations in the RSSI. The values from 1dBm to 10dBm have been tested to determine T_v. While a value, that is too low, triggers wrong detections, persons crossing the monitored area can be missed using a value, that is too high. In our experiments T_v is set to $T_v = 5dBm$ which is at the balance point between the two cases. The complete algorithm can be seen in Figure 2:

The computation of the weighted mean is not suspended during a detection event. If it were, the computed value would not describe the variance of the RSSI anymore, but instead the difference between the current RSSI and the last computed weighted mean. This however is the basis of the mean RSSI based detection.

4.2 Mean RSSI Based Technique

Detection techniques based on the mean RSSI analyse the attenuation of a radio signal caused by the human body. Basically, the mean of all previously collected RSSI values is computed and compared with the current RSSI measured at that time. An event is detected when the difference of the two values is above a certain threshold T_m. For the mean based detection we once more compute a weighted mean applying Equation 2. As done for the computation of the variance the weight factor α is set to $\alpha = 0.9$ in order to weight the current mean with 90% and every new value with 10%. Again, this is done for each of the three channels individually.

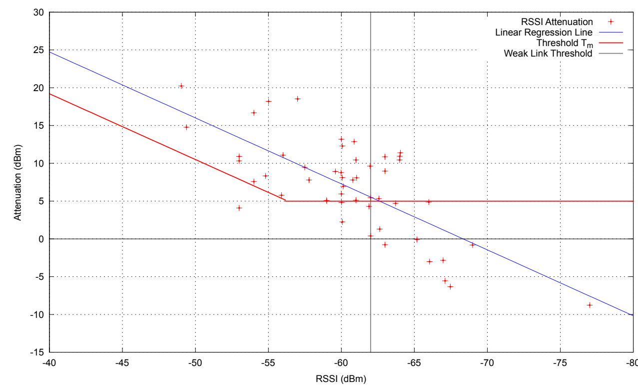


Figure 3. Attenuation of a person standing in a BLE radio link plotted over the received signal strength of the link.

However, the computation of the weighted mean is suspended during a detection event. The RSSI values during a detection event are deviating significantly from the weighted mean in the tranquil phase. Updating the weighted mean during the detection event would change the basis against which the current values are compared and thus corrupt the information about the empty link. As a result, a link could be assumed empty while a person is actually standing inside the monitored area. For the same reason, the RSSI values recorded during the event may also not be used after the event is over, but will instead be discarded.

It is also important to recall that the RSSI while influenced by the distance of the radio nodes is also dependent on the position of the nodes. This is due to the fast fading effect of a BLE radio link as seen in [6]. A radio link can have a weak signal strength either because the sender is far away or because the receiver is at a position where it is affected by fast fading. For this reason, we design our detection threshold T_m to be purely based on the received RSSI not including any information concerning the signal distribution at different distances, like e.g. done in [1]. We accomplish this by designing T_m based on a dynamic threshold T_d, with changing values based on the current RSSI. To determine the function for the dynamic threshold, we perform an experiment comparing the RSSI of an obstructed radio link with the unobstructed behaviour of the same link. For this, we set up one BLE radio link consisting of two nodes, mounted on wooden poles. During the measurement we record the RSSI on all three BLE advertising channels separately. First, we measure the RSSI of the empty link. Then a person is stepping into the monitored area and we measure the attenuation in the RSSI of the now obstructed link. The RSSI is gathered in both cases for one minute. After each measurement, we move the poles to a new position which changes the RSSI on all channels. We repeat this measurement at 17 positions with 12 different distances between the nodes ranging from 0.25m to 4m. The results can be seen in Figure 3.

In this figure, the attenuation in the RSSI is plotted over

Table 1. States of the mean RSSI based detection algorithm

State	Description
0	No detection - empty link
1	Detection - person in link
2	No detection with reduced credibility
3	Detection with reduced credibility
4	Error
5	Calibration

the received signal strength for every measurement. A clear trend is visible, indicating a smaller attenuation in the RSSI, the lower the received signal strength is. This is in accordance with the observations in [8], where a quadratic relationship between the RSSI of a blocked and an empty WLAN link is postulated. When plotted over the received signal strength, a quadratic regression line can be computed. However, the RSSI range we experience during our measurements lies in a section of the quadratic regression that is overlapping the linear regression of the same measurement. Because of this, we can use a linear regression as an approximation of the relationship for all further experiments without decreasing the accuracy of the detection algorithm. The function of the linear regression line computed from the measured attenuation in the RSSI serves as a base for the dynamic threshold T_d of the presence detection. However, the linear regression line is only an average. It describes attenuation in the average case when a person enters the monitored area. We need the dynamic threshold to be smaller than the average attenuation in the RSSI, since we are also interested in detecting events that only cause a smaller than average attenuation. Everything below the threshold is not considered to be a detection event. Thus, we introduce a variable β by which the dynamic threshold is lowered, defining the function for our dynamic threshold to Equation 3,

$$T_d = 0.87 * RSSI_{current} + 59 - \beta \tag{3}$$

in which $RSSI_{current}$ is the current RSSI measured at that time and β the variable lowering the dynamic threshold.

As seen in Figure 3 the curve described by Equation 3 cross the 0dBm line. This is an issue, because it means that there is a set of radio links with weak signal strength whose RSSI does not change when a person enters the link. In Figure 3 it can also be seen that the anti-fading and deep-fading effects described in [20] apply to BLE radio links, when used for presence detection. To account for these circumstances, we introduce a weak link threshold WLT. Events based on radio links with a mean RSSI below this threshold are judged to be not as reliable as events on radio links with a mean RSSI above WLT. The value of WLT is set to the RSSI at the crossing point of Equation 3 with the x-axis, after which the described effects might occur.

Furthermore, if Equation 3 was used as dynamic threshold without further restrictions, it would trigger false detection events on links with an RSSI level in the range of the crossing point. Since the threshold on those links would be set close to zero, even RSSI values that are perfectly in line with

```
for i ∈ {37,38,39} do
    if Channel = i then
        if (State = 0) ∨ (State = 2) then
            Mean^i_current = EQ. 2(Mean^i_old, RSSI^i_current)
            Mean^i_old = Mean^i_current
        end if
        T_d = EQ. 3(RSSI^i_current)
        if Mean^i_current − T_d > RSSI^i_current then
            detectionState = 1
        else
            detectionState = 0
        end if
        if Mean^i_current < WLT then
            if (Mean^i_current − RSSI^i_current > T_g) ∨
              (Mean^i_current − RSSI^i_current < −T_g) then
                detectionState = 3
            else
                detectionState = 2
            end if
        end if
    end if
end for
return detectionState
```

Figure 4. Mean RSSI based detection algorithm.

the mean RSSI computed during the tranquil phase would be seen as detection event. To avoid this, we introduce an additional constraint on the event detection. If the difference to the mean RSSI is smaller than a global threshold T_g, it is ignored and no event is triggered. The threshold T_m now follows Equation 4.

$$T_m = \begin{cases} T_d, & \text{if } T_d > T_g. \\ T_g, & \text{otherwise.} \end{cases} \tag{4}$$

Based on this rationale, we introduce six possible output states for the detection algorithm, as seen in Table 1.

State 0 is the no-detection state for links with RSSI values above WLT. Respectively, state 1 is the detection state for this case. State 2 is the no-detection state for links with a RSSI below WLT and state 3 the detection state. We assume a reduced credibility for events of the last two types. State 4 is reserved for invalid operations and will be entered in the case of an error. State 5 is the calibration state of the system. Since the weighted mean is computed for all three channels separately, if an event was to occur before a channel had a chance to receive a message, the initial computation of the mean would not be based on the tranquil phase when the link is empty. This would influence the detection algorithm by introducing wrong values for the weighted mean to compare against. In the worst case, if a very low RSSI value were chosen as the mean, the system could wrongfully identify RSSI values of an empty link as detection events. This would stop the computation of the weighted mean and lock the system in a state of constant detection. To avoid this, the detection algorithm stays in the calibration state 5, until at least one message was received on each channel. The duration of the calibration phase depends on the value of the scan

Figure 5. Set-up of the prototype queueing system.

interval set for the BLE radio link, after which the channel is switched. While the algorithm still performs correctly even without a calibration phase (assuming that no disturbance of the system occurs, before each channel had a chance to set its mean) the calibration phase was introduced as an additional measure to secure the robustness of the system.

After the initial calibration, the mean based detection operates as follows: When a new RSSI value is received, it is first checked, whether the system is in a tranquil phase without detection. If so, a new weighted mean and the threshold T_m are computed. If the current RSSI is smaller than the weighted mean subtracted by the threshold T_m, but greater than the weak link threshold WLT, a new state 1 detection event is triggered. If the current RSSI is lower than WLT, it is checked, whether an event on an anti-fading or deep-fading link has occurred, which we then assign a reduced credibility. This is done by checking whether the mean minus the current RSSI is larger than the global threshold T_g, or, in case of a deep-fading link, is smaller than $-Tg$. In both cases a state 3 event is triggered. The complete mean based algorithm can be seen in Figure 4.

5 Evaluation

We evaluate the extended detection techniques in a laboratory-setup, as seen in Figure 5. Radio nodes are mounted atop wooden poles to simulate a setup similar to that of a corridor framed by cord-connected barrier poles as found in waiting lines e.g. in airports or coffee shops. The monitored area in our experiments is a corridor of 1x4 meters, comparable to a queueing area. The corridor is crossed by four radio links, each made from two nodes on opposite sides of the waiting line. We assume the positions of the nodes are known and every node is aware the ID of its partner node on the other side of the corridor.

We define an event as a person crossing the monitored area of one radio link. We further define a match as an event, that has been detected by the used algorithm within 0.6s difference to a recorded ground truth. A false negative is defined as an event that has not been detected, and a false positive as a detection without the monitored area being crossed. To evaluate the performance of the different parameter we use the metrics of *precision*, *recall* and the *F1-score*. The precision is a measure of how many of the detected events are actual matches. It answers the question whether the detected events are correctly identified. The precision is computed following Equation 5.

$$precision = \frac{truepositives}{truepositives + falsepositives} \tag{5}$$

The recall is a measure of how many matches out of all events have been identified. It indicates whether an event has been missed. The recall is computed following Equation 6:

$$recall = \frac{truepositives}{truepositives + falsenegatives} \tag{6}$$

The F1-Score is a combination of both and is computed following Equation 7:

$$F1\text{-}score = 2 * \frac{precision * recall}{precision + recall} \tag{7}$$

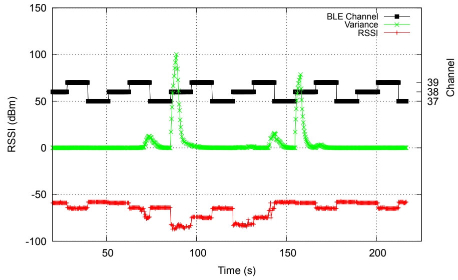
When entering or leaving the monitored area a person's body is not fully emerged in the radio link. In this transition phase changing attenuation values e.g. caused by arm or leg movement can trigger multiple detections for one event. To avoid miscounting the events in the evaluation, multiple detections are combined into a single event if they occur in an interval of 1s after another. As described in Section 4.1, this value is again based on the time it takes a person to cross the monitored area of a link.

As ground truth of the detection, we use a laser-beam type system against which we compare the detection algorithms. For this, we aim wall-socket powered laser-pointers, also mounted on adjustable wooden poles, at the light sensors of smartphones. If a person enters the monitored area of our prototype set-up, the presence of her body inflicts disturbances in the radio link of the BLE transceivers, which will cause a detection event. Simultaneously, the beam of the laser-pointer is interrupted and a ground truth detection event is triggered. Both systems send their events to the same sink, connected to a PC. Whenever a message from the detection system or the ground truth system is received, it is combined with a timestamp generated by the PC, so that the messages can be set in direct relation to each other.

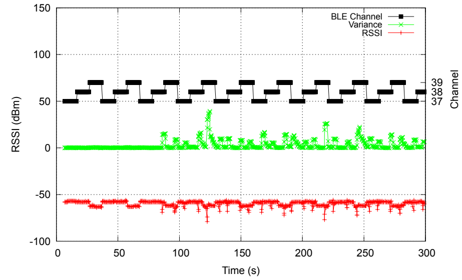
5.1 Implementation

To establish the radio link, we use the ATMEL Xplained Pro evaluation platform, which is equipped with an ATMEL SAMB11 Bluetooth 4.1 module, including an integrated MCU and a BLE transceiver. Messages are sent on the three primary BLE advertising channels from the transmitter to the receiver of one radio link. The transmitter is mimicking the behaviour a BLE beacon by broadcasting one message every 100ms. The receiver receives all messages and filters them for the ID of its partner node on the opposite side of the corridor. In our experiments, scan interval as well as scan window of the BLE receiver are set to the maximum value of 10.24s. With this, the calibration phase has a duration between 10.25s to 20.49s, depending on the timing of the first message in the first scan interval.

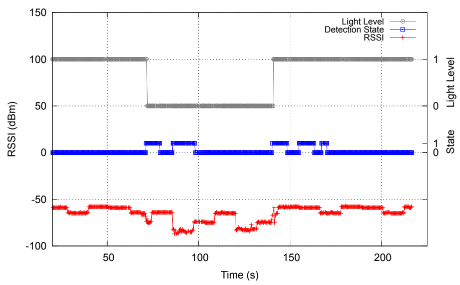
For the receiving node it is not possible to derive the channel on which the message was sent from the link layer of the



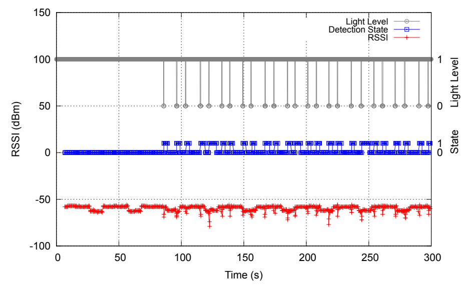
(a) EX1: Variance when standing in the link.



(b) EX2: Variance for the first twenty-five link crossings.



(c) EX1: Detection compared to the ground truth.



(d) EX2: Detection compared to the ground truth.

Figure 6. Results of the variance based detection experiments EX1 and EX2.

BLE transmission. However, it is possible to set the channel on which the advertisement messages are sent on the transmitter. Exploiting this, we include the information about the current advertising channel into the payload of each message. Then, we send exactly one advertisement message and stop the BLE advertising. We repeat this process for every message while cycling through the advertising channels. This way, in each message the information about the channel on which it is send is accessible to the algorithms. By modifying only the transmitter, any BLE capable receiver can be used to obtain this information without the need for a special API.

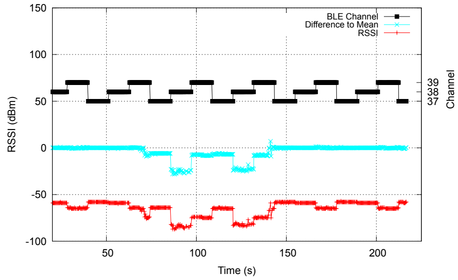
5.2 RSSI Variance Based Detection

To determine the detection performance of the extended techniques and their use in queueing systems, we first analyse the effects of a person in a single BLE link. For this, we perform two experiments with different challenges for the algorithms. For each experiment, we analyse the behaviour of the RSSI and compute the mean and the variance. In the first experiment, $EX1$, a person is entering the BLE radio link, keeps standing still in the line of sight between the radio nodes for one minute, and then leaves the link. The experiment tests the algorithms ability to handle continuous attenuation and is repeated 5 times. In the second experiment $EX2$, a person is crossing the radio link multiple times at a constant speed. The speed is regulated by markers on the floor and a metronome. The metronome gives a beat of 60 beats per minute, while the markers are 50cm apart. Every time a metronome beat is heard, the person takes a step on a marker. This way a speed of 0.5m/s is maintained. For this experiment the link is crossed at least 50 times, while the algorithms ability to detect movement is tested.

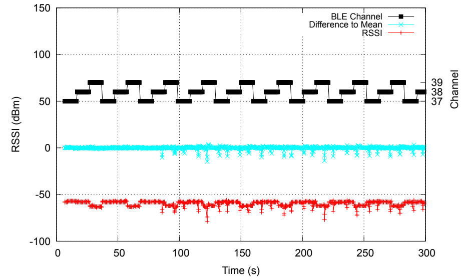
An exemplary result of the first experiment $EX1$ using the variance based algorithm can be seen in Figure 6. In Figure 6(a) variance and RSSI follow the scale of the left y-axis. The variance is downscaled by factor 250 to fit the graph. The information about the BLE channel, on which the current message is received, is on the right y-axis. As seen in the figure, each of the three BLE channels has its own mean RSSI level, as described in [7]. This is accounted for in the calculation of the weighted mean as described in Section 4.

Figure 6(c) compares the result of the detection based on the variance algorithm with the ground truth. The light level used as ground truth, and measured by the light sensor, follows the scale of the upper right y-axis. Its main purpose is to indicate whether a person is in the monitored area. A low light level of '0' means that the beam between laser and light sensor is interrupted and a person is standing in the link. A high light level of '1' indicates that the laser beam is not interrupted and the link is empty. The detection state follows the lower right y-axis, while the RSSI follows the left y-axis.

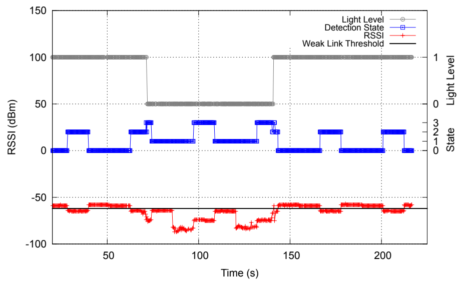
As seen in Figure 6(a) the RSSI is influenced for as long as a person is standing in the link. However, the RSSI only experiences high variance when the person is entering or leaving the monitored area. During the period the person is standing motionless, the recorded variance is close to zero. This is because the variance is induced by fluctuations in the RSSI value. Even if a person is attenuating the radio link, for as long as the magnitude of the attenuation does not change, there is no variance. That is why during our experiment there is a duration in which no variance based detection is registered, despite a person still standing in the monitored area. The spikes in the variance, visible around 90s and 160s, are caused by the switch from one BLE advertising channel to



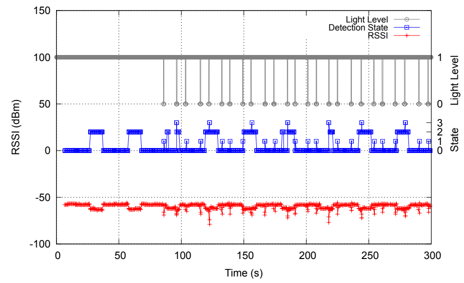
(a) EX1: Difference to the mean RSSI when standing in the link.



(b) EX2: Difference to the mean RSSI for the first twenty-five link crossings.



(c) EX1: Detection compared to the ground truth.



(d) EX2: Detection compared to the ground truth.

Figure 7. Results of the mean based detection experiments EX1 and EX2.

the next. The transition from the unobstructed to the obstructed link occurs between two scan intervals on the same channel. Because of that, there is a difference in the mean RSSI of that channel. The RSSI in the interval while the link is not obstructed is much higher than the attenuated RSSI of the obstructed link. This causes the RSSI values in the sliding window to be dissimilar and thus increases the variance.

Figure 6 also depicts an example of the first half of the second experiment $EX2$ for the variance based algorithm. In Figure 6(b) information about the BLE channel, the variance and RSSI are shown, whereas Figure 6(d) gives a closer view on detection state, RSSI and ground truth. Out of the 52 times the link was crossed in total, 51 events have been correctly identified by the variance based algorithm and no false positives have been recorded. With this, the variance based algorithm achieves a precision of 100%, a recall of 98.1% and a F1-score of 99%. Since the person crossing the link is in constant motion, the variance based algorithm is well suited to detect these events.

However, as observable in Figure 6(d) as well as in Figure 6(a), there is a delay after a person leaves the monitored area, before the variance returns to the level of an empty link. As mentioned in Section 4, this is caused by the sliding window used for the variance computation. The attenuated RSSI values recorded during the detection are still affecting the variance computation until they have been replaced. Since the sliding window has $var_{window} = 10$ slots, and messages are sent every 100ms, the experienced delay is 1s. This effect reduces the responsiveness of the variance based algorithm. It also could cause some issues if the variance based detection is used during the operation of a queueing system. If two people entered the waiting line quickly after another, the delay could cause the system to only recognise one event, instead of two, thus missing the second person.

5.3 Mean RSSI Based Detection

To use the mean based detection algorithm, we first need to calibrate the dynamic threshold T_d, because it influences the accuracy of the algorithm. For this, we optimise the values for β, by which the linear regression line is lowered, and for the global threshold T_g, describing the minimum difference between current RSSI and the weighted mean. We test the mean based detection algorithm in the same two experiments $EX1$ and $EX2$ and on the same datasets we use for the variance based algorithm: First, a person is standing in the link, then the link is crossed by a person walking at a constant speed.

An example of one of the five runs of the first experiment can be seen in Figure 7. The RSSI, the difference to the mean RSSI and the BLE channel are shown in Figure 7(a), while Figure 7(c) shows the RSSI, the detection state and the ground truth. Additionally, the weak link threshold WLT, below which we deem the detection to be less reliable, has been included in the graph.

As can be seen, when a person enters the monitored area, the RSSI drops which is registered by the algorithm. The state of the system is changed from state 2 *'no detection with reduced certainty'* to state 3 *'detection with reduced certainty'*, since the RSSI level of the link is below WLT. When the channel changes and the RSSI level is above the threshold, the detection state changes to state 1 *'detection'*. After the person leaves the link, the detection state goes back to state 2 *'no detection with reduced certainty'*, or in the case of the channel above the threshold to state 0 *'no detection'*. The person is detected for the complete duration of their stay in the monitored area, even while standing motionless.

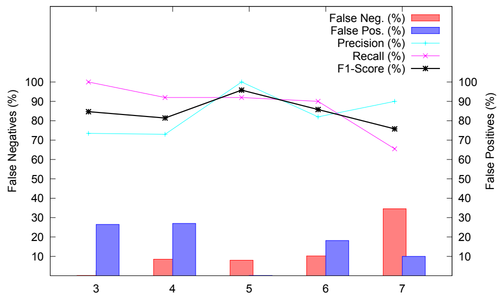


Figure 8. Detection performance when changing T_g.

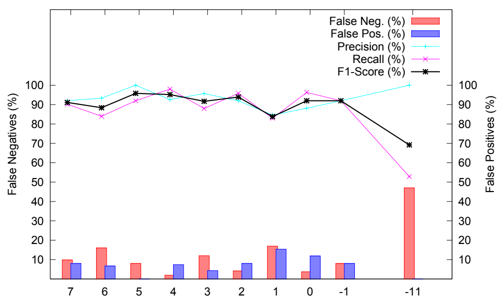


Figure 9. Detection performance when changing β.

Figure 7 also depicts the first half of an example for the walking experiment $EX2$, in which the radio link is crossed 52 times. The graph is plotted following the description for the standing experiment of the mean RSSI based detection with Figure 7(b) showing the difference to the mean RSSI and Figure 7(d) depicting the comparison between detection state and ground truth. Like in the case with the variance based algorithm, 51 out of the 52 crossings have been detected. (It is interesting to note that the event, which has not been detected, is not the same for both algorithms.) With this, the mean RSSI based detection algorithm also proofs suitable for passive presence detection.

To further evaluate the influence of the global threshold T_g, we first set β to 5dBm, which lowers T_d by the magnitude of one standard deviation of the computation for the average linear regression. This sets the summand of the linear regression in Equation 3 to −54dBm. Afterwards we perform an experiment with a person walking through the link at least 50 times. Each time we vary the parameter of the global threshold T_g in steps of 1dBm. This way we perform five measurements covering the range between 3dBm and 7dBm. The results of the experiment can be seen in Figure 8.

As it is shown in the graph, there is a trade-off between a too low and a too high global threshold, when comparing the current RSSI and the weighted mean. If the threshold is set too low, small divinations in the RSSI will already be registered as events and cause a high false positive rate. Because of this a threshold of 3dBm, for example, has a high recall but only a precision of 73.5%. A too high threshold however will cause some events not to be detected, resulting in an increased rate of false negatives. Because of this, a threshold of 7dBm above the mean has a high precision but only a recall of 65.5%. A threshold of 5dBm is in between those two and has the highest overall F1-score with 95.8%. The recall is at 92%. The precision is at 100%, since no false positives were detected in this run of the experiment. Because of this, we set $T_g = 5$dBm for all further experiments.

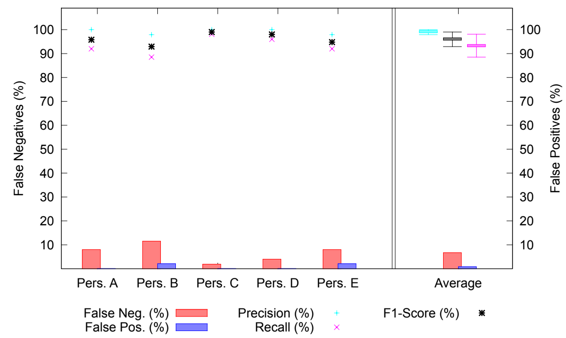


Figure 10. Detection performance for different persons.

Table 2. Performance parameters for different persons.

User	Precision (%)	Recall (%)	F1-Score (%)
A	100	92	95.8
B	97.9	88.5	92.9
C	100	98.1	99
D	100	96	98
E	97.9	92	94.8
Average	99.2	93.3	96.1

In order to evaluate the influence of β, we perform an experiment with ten measurements, during which in each run the radio link is crossed at least 50 times walking at a constant speed. We assign the values between +7 and −11 to β. This sets the additive part of Equation 3 in the range between −52dBm and −70dBm. We expect that by increasing the value of β and thus lowering the dynamic threshold, more events will be detected. The results of the experiment can be seen in Figure 9.

As seen in the figure, changing the value of β in the range between +7 and −1 has no clear influence on the detection results of the mean based algorithm. When checking the RSSI levels of the measurements, we see that about two thirds of all received RSSI values are at a level, at which T_m equals T_g, following Equation 4. β is not directly influencing the global threshold, but only adjusts the RSSI level, at which the detection algorithm switches to use T_g instead of computing T_d (as seen in Figure 3). These circumstances explain the indifferent behaviour. However, we can demonstrate the influence of β when further decreasing its value. When β is set to −11, setting the additive part of Equation 3 to −70dBm, the threshold T_m is exclusively using T_d. This causes 47% of the events to be false negatives, since the threshold is set too high. Alternatively, increasing β would lower the threshold T_m in the range of links with high RSSI values around e.g. −30dBm, and would thus increase the occurrence of false positives. However, since a value for β of $β = +5$ is suitable for the RSSI spectrum experienced on our BLE radio links and corresponding to the standard deviation of the computation for the average linear regression, β is set to +5 for all

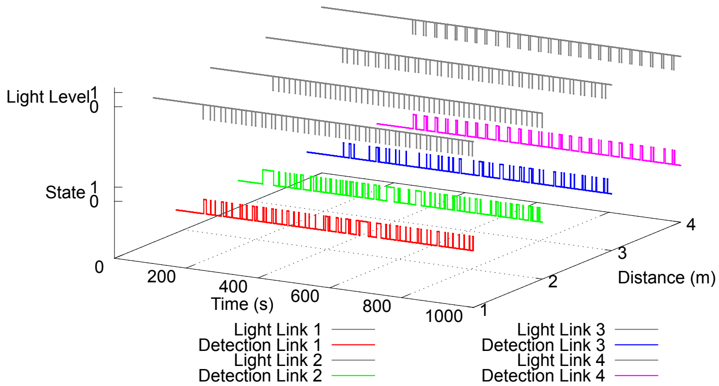


Figure 11. 3D representation of the detection events in the queueing system.

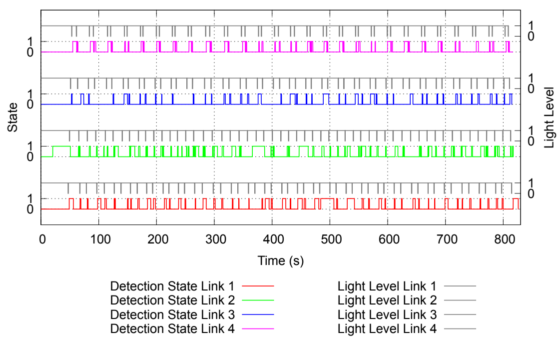


Figure 12. 2D representation of the detection events in the queueing system.

Table 3. Performance parameters for the radio links in the queueing system.

Link	Precision (%)	Recall (%)	F1-Score (%)
1	98.1	94.4	96.2
2	96.1	90.1	93.0
3	100	87.0	93.1
4	100	98.2	99.1

further experiments. This lowers the dynamic threshold T_d by 5dBm. Since β has been determined, we can now compute the crossing point of Equation 3 with the x-axis and set the value for the WLT to -62dBm in all experiments. Setting $\beta = 5$ and $T_g = 5$ results in an F1-score of 95.8%, a recall of 92%, and a precision of 100% in our test experiments.

5.4 Queueing System Evaluation

Our experiments have shown that both RSSI variance based and mean RSSI based presence detection algorithms can be extended to work with BLE. However, while the variance based approach excels at detecting movement in the monitored area, it shows a deficit at detecting motionlessly standing persons. Because of this issue, we focus our attention on the RSSI mean based algorithm for the design of our prototype queueing system.

To further analyse the robustness of the mean RSSI based detection algorithm, we repeat experiment $EX2$ with different persons. Each person is asked to pass the monitored area between the BLE nodes 50 times again with the same speed. The results can be seen in Figure 10. As shown, there is a slight variance in each measurement, however, the accuracy in all runs is always above 92%. The F1-score averaged over all persons is at 96.1% with a maximum 99% of and a minimum of 92.9%. The values for recall and precision can be seen in Table 2. This demonstrates that the mean RSSI based algorithm can cope with different persons.

Finally, we use the extended mean RSSI based algorithm to monitor detection in a queueing system scenario using all four links of our experiment set-up. Doing so, we simultaneously test the algorithm at different spatial positions. In this experiment the receiver of a radio link only transmits changes in the state of the detection algorithm to the common sink, like the ground truth system did before. The analysis, whether a link has been crossed, is distributively performed on the nodes. The sink itself is connected to a PC, on which the algorithm state of each link and the respective ground truth are recorded. The transmission to the sink uses a connectionless BLE protocol with acknowledgements. Like in experiment $EX2$, a person is walking through all four links at a constant speed for at least 50 times. The results of the experiment can be seen in Figure 11. The figure shows the output of the complete queueing system over time. For clarity reasons, both state 0 and state 2 are plotted as '0' on the z-axis, and state 1 and state 3 as '1'. The light values of the ground truth are set to the values of '0' for detection, and '1' for no detection. The y-axis depicts the distance of the links to each other. As can be seen, the links consecutively record a crossing of the monitored area, when a person enters the system, which corresponds to the ground truth plotted above. To better visualise the detection events matching the ground truth, the events of all links have again been plotted beneath each other two-dimensionally in Figure 12. Almost all events are detected and transmitted to the PC for further possible processing. The performance of the four links, measured by the F1-score, is 96.2%, 93.0%, 93.1% and 99.1% respectively from link 1 to link 4 as seen in Table 3. This shows that a mean RSSI based queueing system can accurately detect different persons and works at different positions. The events transmitted can be used to build a queueing system on top of the detection algorithms, analysing the performance parameters of a waiting line.

6 Conclusions

In this work we extend techniques for passive presence detection to work with BLE radio links for the use in waiting lines. A RSSI variance based and a mean RSSI based algorithm are evaluated in experiments with a mobile prototype queueing system. We demonstrate that both techniques can be extended to account for the mandatory frequency hopping implemented by BLE. For this purpose we include the information about the current advertising channel into the payload of each message.

While the algorithm based on the variance of the received RSSI achieves a high detection performance of up to 98% detecting walking persons, it strongly depends on the observed motion. If the person in the radio link stands motionless, the algorithm's detection will be insufficient. In comparison, the mean RSSI based algorithm only achieves a performance of 96.1% when detecting walking persons. However, the algorithm also detects persons standing in the monitored area. When used in the prototype queueing system, the mean based algorithm is capable of detecting persons in four radio links simultaneously.

Furthermore, we find that RSSI based algorithms in general have an advantage compared to common beam-type detection systems used in waiting lines. RSSI based systems are omnidirectional and thus have a very short set-up time, which makes them ideal to be deployed on top of e.g. barrier poles of the queueing system. Beam type systems either have to be wall mounted, which reduces the option of quickly redeploying a system, or have a time-consuming adjustment phase. In fact, during the set-up of out measurements, aligning the laser-beam based ground truth system onto the light sensor took the longest time of up to 35 seconds per link. Additionally, a laser will be immediately misaligned if a barrier pole is moved.

Since our experiments have shown that an RSSI based approach is feasible to realise a queueing system, we now aim to expand on this. We plan to introduce pattern detection algorithms to analyse the events transmitted to the PC to make estimations about the number of people and the waiting time in a waiting line. We further want to enhance the portability of the prototype by introducing a self-calibration to the queueing system, that identifies the layout of the current deployment. Doing so, we ultimately hope to use our system in combination with free movable barrier poles which would be required for a practical commercial application.

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