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Detection of pause in a pedestrian's movement on a linear walkway using Bluetooth Low Energy Received Signal Strength Indicator

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***Abstract*—In recent years, Bluetooth Low Energy (BLE) has amassed significant attention in several applications. Its potential, however, remains largely unexplored for understanding pedestrian behaviour. This study focuses on investigating the potential of BLE in identifying pedestrian activity in an outdoor linear walkway. We specifically examine the likelihood of detecting pauses in the movement of pedestrians on a linear walkway using the strength of the signals obtained from a BLE device carried by the pedestrian. To accomplish this, a volunteer pedestrian intentionally pauses at selected points on the chosen walkway for varying predetermined intervals. The obtained data was conditioned using a polynomial curve to reduce the impact of anomalous data and was subsequently used to detect flatness in the trend of the signals to identify a pause. This flatness was identified using a sliding window standard deviation (SD) calculation over the curve obtained through polynomial fitting. Our results indicate a strong likelihood of detecting long pauses in a pedestrian's journey.**

***Index Terms*—Bluetooth Low Energy, Walking, Privacy Preservation**

I. Introduction

BLE is increasingly employed in a number of application areas in addition to its original intended use to enable low-energy [1] communication between devices. The use cases for BLE now span across several domains including positioning and localisation [2]–[7], activity recognition [8], [9], and resource management [10]–[12]. Understanding pedestrian behaviour is one such problem domain that can benefit from the use of BLE. While other technologies such as imaging sensors have been employed to study pedestrians and crowds for many years, the introduction of strict privacy regulations such as General Data Protection Regulation (GDPR) has brought the privacy preservation aspects of these established technologies into focus. This presents an opportune moment to investigate the effectiveness of alternative, more privacy-preserving technologies to understand pedestrian behaviour. As we shall see in II, the design of the BLE protocol offers features that are useful to ensure privacy preservation. Despite the advantages offered by BLE, it is challenging to extract conclusive information about the behaviour of pedestrians carrying BLE devices. This is because this method relies on deciphering complex human activity from relatively limited data, such as the strength of the received BLE signals. Moreover, the 2.4 GHz frequency range in which BLE operates is prone to influence by external environmental factors such as the presence of other pedestrians.

In this paper, our objective is to develop a BLE-based method that can inform whether or not a pedestrian pauses while walking along a linear walkway. Such information could shed light on the utilisation of a monitored space by its users, and subsequently, form the basis for a decision support system to aid data-driven (re-)development plans. To achieve this, we aim to study different durations of pauses in pedestrian movements to identify if limited information obtained from the signals of BLE device can be used to indicate a pause in a pedestrian's movement. Section II discusses the background of the technology and the topic. We outline the rationale and elucidate the experimental setup in section III. We then provide the obtained results in section IV and discuss the findings and future directions in section V.

II. Background

BLE is an appealing technology choice for use in pedestrian behaviour analysis. While the technology cannot directly capture useful information to decipher behavioural traits, the data acquired using BLE can be extrapolated to interpret the likelihood of occurrence of a particular behaviour. While predicting only a likelihood sounds somewhat restrictive to overarching goals such as data-driven decision-making, it also aligns with the agenda of privacy preservation. With a sufficient understanding of the technology and its usage, like this study, techniques that provide more confident assertions about general patterns of behaviour by groups of users can be anticipated.

The BLE protocol defines four different roles for a device which are discussed in [13]. A role called an *Observer* prevents

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the device in this role from establishing connections with any other device. Therefore, an Observer can only discover the presence of nearby BLE-enabled devices that are in an *Advertising* state. In an Advertising state, a BLE device emits messages necessary to establish a connection. Another role, a *Broadcaster*, makes a BLE device incapable of establishing a connection. A Broadcaster is always only in an Advertising state. The remaining two roles, *Central* device and *Peripheral* device can establish a one-to-one connection with each other. A Central device listens for advertisements and initiates connections, whereas, a Peripheral device advertises and accepts or refuses a connection request. The use of an Observer as a listening device ensures that irrespective of the role of the nearby advertising device, a connection will never be established, therefore adding another layer to ensure data protection. Additionally, since the advertising devices are bound to transmit messages in their local vicinity, a Broadcaster will continuously transmit packets whereas a Peripheral will transmit packets only if the user of the device has switched its discoverable mode on, BLE can also be employed for *opportunistic* monitoring [14].

Finally, a link layer feature in the BLE core specification [15] enables *whitelisting*, where advertisement packets from devices not specified in the whitelist are discarded by default. This feature allows the technology to fully embrace consensual monitoring. Hence, a thorough understanding of the application of BLE for pedestrian behaviour monitoring is suited to regulated privacy-preserving data collection and analysis.

As briefly mentioned in section I, despite advantages, BLE is difficult to employ for non-traditional uses due to the factors including limited information, the vulnerability of its signals to factors such as metal objects in the environment [16] and weather conditions [17], and unreliability at greater distances [18]. Like any other high frequency Radio Frequency (RF) signal types, BLE signals are also prone to long-distance path loss and fading [19]. The computational capability of the Observer and the number of tasks it performs may result in delayed processing of the intercepted which adds another limitation [20].

Despite all the challenges, the use of BLE has gradually increased in pedestrian-related research in recent years. This includes research to create accessible sidewalks for blind and visually impaired (BVI) pedestrians [21], localisation and alerting visually-impaired pedestrians at intersections [22], vehicle-pedestrian collision warning systems [23], [24], bicycle-pedestrian safety systems [25], and pedestrian flow detection in urban public spaces [26]. However, there are many aspects of pedestrian behaviour that need addressing for a holistic pedestrian behaviour monitoring system.

A comprehensive pedestrian behaviour monitoring system is essential to tackle the challenges posed by rapid urbanisation [27] on already resource-constrained cities that are now suffering from a plethora of problems including social segregation, pollution, degrading biodiversity [28]. An extensive understanding of urban topology can aid in (re-)development plans that may address these issues. To understand the usage of spaces, we must comprehend the breadth of behavioural aspects of pedestrians. As [29] describes, behaviour can be categorically represented on a *temporal scale* in three ways that relate to the choices a pedestrian makes. These is *strategic level behaviour* where a choice of activity, destination and their scheduling is concerned, *tactical level behaviour* which pertains to the choice of route and exit, and finally, *operational level behaviour* which concerns choices related to physical movement. The work outlined in this paper is an attempt to primarily shed light on the operational level behaviour of pedestrians, where the inferences may describe the local interaction of pedestrians with spaces, objects, information, and/or other pedestrians.

III. Methodology

A. Rationale

The Received Signal Strength Indicator (RSSI) of a BLE signal depends on the distance between the advertising device and the intercepting device [30]. In this work, the former is called the *Broadcaster* and the latter, the *Observer*. This means that if the distance between the two devices is to remain constant, the Received Signal Strength (RSS) value should remain constant. However, as discussed in section II, the strength of the signal is susceptible to many factors in the environment, and hence, in the real world, the RSS values will fluctuate even when the distance between the two devices is kept constant. Notwithstanding this, the RSS values can indicate an unchanging distance between the two devices because the fluctuation in the RSSI will be restricted to a narrow range. This is because when the distance between the two devices is constant, the RSSI is only affected by the noise and not by varying distance between them. Therefore, if we observe the pattern formed by the RSS values against time, we should be able to recognise flatness, or a plateau, in the graph to signify that the distance between the devices remains constant. When the distance between the Observer and Broadcaster stops varying, the multi-path components of the 2.4 GHz signal experience a Doppler shift [19], leading to a delay in the formation of a flatness or plateau. Moreover, if the duration of the pause is short, the resulting feature in the RSS values may not be recognisable. This study aims to detect pauses in pedestrian movement using the hypothesis of flatness in RSSI and determine whether short pause durations on the walkway will result in a noticeable flatness.

B. Experimental Setup

A simple and inexpensive design to enable an easy replication of the experiments was a priority. Our methodology leans towards Privacy-by-Design (PbD) principles to minimise the chance of capturing personal information. The following subsections elaborate on our experimental setup.

1) Devices: Our system is comprised of three elements, Observer, Broadcaster, and Geo-locator. We use a Raspberry Pi (RPi) 4B as our Observer because it is sufficiently capable of running a script for observing the *Advertisements* and subsequently, identifying the RSS values. It also features a BLE 5.0 chipset which means no additional component is required to use it as an Observer. We placed the RPi inside a high-density plastic enclosure, powered by an off-the-shelf portable power bank [31]. This study follows the same architecture as illustrated in [32] and [13]. On the software front, a Python script is used to monitor the signals emanating only from a single white-listed Broadcaster. This ensures a PbD approach to the system's design. The RSSI and SD of the entire observation period are then stored in an *InfluxDB* database. A Ruuvi Tag [33] was chosen as the BLE Broadcaster. It advertises twice every second. For the geo-locator, we employed a mobile phone app called *Blue Dot* [34]. This app features a button which when pressed, informs the connected Bluetooth (BT) device of its state change. Another Python script was designed to interpret the meaning of a button press to indicate a pause and resumption of the walk by the pedestrian. The occurrences of pause and resumption, along with their respective timestamps were stored in another *InfluxDB* database and then used as a means of establishing a ground truth in this study.

2) Location: The selected experiment location is a rarely used area beside an office building. A wall outside the building offered a suitable structure for deploying the Observer. The less trodden area results in less likelihood of the introduction of noise that may arise due to signals reflecting off other occupants in the space. This area has no defined walkway and allowed us to mark out our own at any chosen distance from the wall and hence, from the Observer. Markers were laid at the starting point of the walkway, called *Start*, the end point of the walkway, *End*, and at a point 6 metres away from *Start*, called *Approach*. These markers aid the volunteer pedestrian's linear movement and are also used to label the exact point for pause. Figure 1 illustrates the location of the experiments.

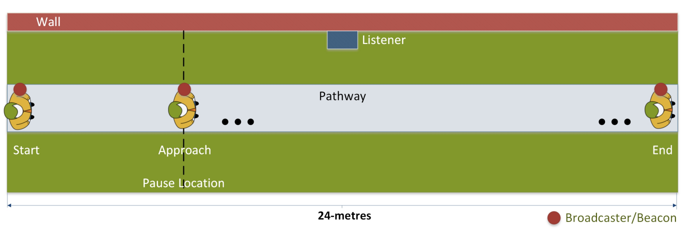


Fig. 1: Experimental location and setup

3) Experiment: For the experiments, a volunteer pedestrian walked on the linear walkway described in III-B2, from *Start* to *End*. This linear walkway is situated 3 metres away from the deployed Observer. The pedestrian set off from *Start* in the direction of *End* but paused at a point, named *Approach*, which is 6 metres away from *Start*. The duration of the pause was varied between 5 seconds, 15 seconds, and 25 seconds. For each pause duration, we repeated the walk four times. Hence, a total of 12 individual cases are considered in the experiment. The Broadcaster was held by the pedestrian facing towards the Observer, hence in line of sight (LoS) of the Observer.

4) Analysis Technique: We opted for a two-step process to analyse the data: curve interpolation followed by windowed SD. Curve fitting provides an estimation of a curve representing the trend of the RSS values. The windowed SD was then used to calculate the SD on segments of the resulting curve. This allows us to identify in which region of the curve the trend flattens.

1) *Curve Fitting*: Since the RSSI is sensitive to any change in the environment, the RSS values fluctuate. However, this fluctuation is mostly within a range which is dependent on the distance between Observer and Broadcaster, and the presence of any obstacles in the signal path between the two devices. Also, we occasionally find anomalous readings which could be due to stray signals arriving at a later time than expected. A curve interpolation estimates a curve that follows the trend of those discrete data points using a polynomial function as seen in equation 1, hence diminishing the effect of anomalous data points, as demonstrated in figure 2. As we can see in the figure, the curve gravitates toward the anomalous reading at the 18^{th} sample however, the effect of this anomalous reading on the curve is reduced. To choose a suitable order of polynomial for our data, we calculate the sum of squared errors (SSE). SSE evaluates the squares of the difference between each estimated data point obtained through polynomial fitting and the original RSS values and adds those values. This is shown in equation 2. A comparison of SSE values of curves resulting from varying the order of the polynomial is used to obtain the best-fit curve. It is essential to note that the RSS values in all the graphs presented in this study are inter-connected using a line segment only for comprehension. There is no certainty that the same line segment would be observed if there were additional RSS values obtained between two consecutive RSS values.

$$p(x) = p_1 x^n + p_2 x^{n-1} + ... + p_n x + p_{n+1} \quad (1)$$

$$SSE = \sum (\hat{y_i} - y_i)^2 \quad (2)$$

where $\hat{y_i}$ is estimated data point obtained from polynomial, and y_i is the original RSSI.

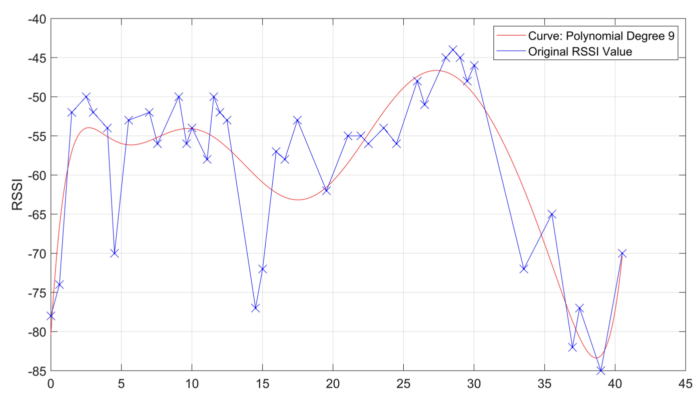


Fig. 2: Curve Fitting for Example RSS Values

2) *Sliding Window SD*: A sliding window on the curve that arose from polynomial curve fitting is used to calculate the SD. This allows for the observation of temporal changes in the trend of RSS values. This sliding window is based on time rather than number of samples. For instance, a window size of 4 denotes a window of 4 seconds and all the data within this segment is used to calculate the SD. The choice of time-based windows ensures that we do not lose any information from the collected RSSI, as explained in the *Results* section, IV. Sliding windows start at the very first RSS value in the entire journey and advances by a step of 1 second. This window is used to compose a set of RSS values located inside the window. Equation 3 represents this process. On each set obtained through the sliding window, SD is calculated as specified in 4.

$$SW(n) = \bigcup_{n=2}^{10} \{R[t : t+n-1] \mid t = 0, 1, \ldots, |R| - n\} \tag{3}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(SW_i - \mu_{SW})^2} \tag{4}$$

where $SW(n)$ is the sets formed by the sliding window, $\cup$ represents the union operation that combines the sets formed, n is the size of window varying from 2 to 10, R holds the RSS values, t indicates the starting position of the sliding window ranging from 0 to $|R| - n$, and $|R|$ signifies the number of elements in R.

3) *Pause Detection and Fine Tuning* Pause detection through examination of RSS values is a simple threshold function. Any value of SD that falls below the threshold is accepted as a pause, as seen in equation 5.

$$P_n = \begin{cases} true & if SD_n < thresh \\ false & if SD_n \geq thresh \end{cases} \tag{5}$$

Fine-tuning of detection is then performed by calculating the duration of each detected pause. If the detected pause duration is less than 3 seconds, we eliminate that from the detected pauses. This allows us to further prevent the effect of any remnant of anomalous data in the interpolated polynomial curve to cause false positives.

4) *Ground Truth*: To validate whether the pause detected by our technique coincides with where the pause actually occurred, we used the timestamp of the button the volunteer pedestrian pressed using the *Blue Dot* app to confirm their pause and resumption of their journey.

IV. Results

Flatness in a plot of RSS values against their arrival time signifies a sustained period where those values oscillate in a narrow range, that is, a sustained plateau in the resulting plot. This therefore can be identified using a sliding window over the obtained RSS values to calculate SD. If the value of SD is below a *chosen* threshold, it should signify flatness or the formation of a plateau. Now, the important concerns to address are, **a.** the optimum window size for the sliding window, and **b.** the threshold value to compare the calculated SD against. However, before determining the optimal window sizes and subsequently, detecting pauses, we must consider a way to mitigate the effect of fluctuations in the RSS values. Therefore, we first applied the raw data to a polynomial equation to interpolate a curve that fits the trend of RSS values.

A. Polynomial Curve Fitting

As stated in the *Methodology* section, III-B4, we evaluated the fitness of the curves that were produced from polynomials of varying degrees. We varied the degree of polynomials from 2 to 9 for each of the four repetitions of each pause duration: 5, 15 and 25 seconds. The SSEs were then calculated for each of the resulting curves and a polynomial with degree 9 was selected as it demonstrated the lowest SSE parameter, and hence the best fit. This is shown in figure 3. The curves resulting from selected degree 9 polynomial fitting in figure 4 are overlaid on the original RSS values.

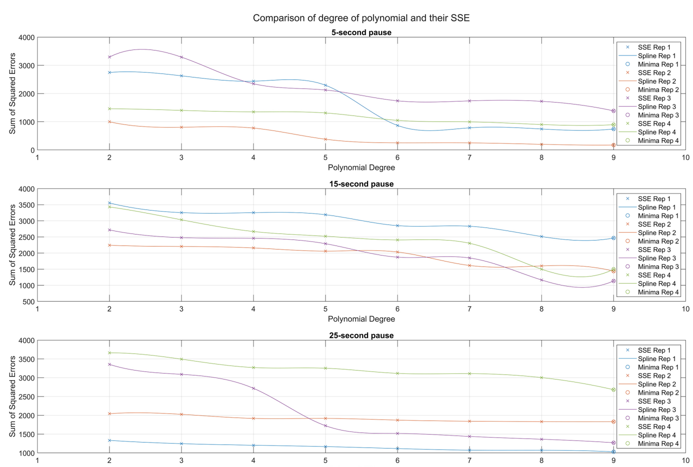
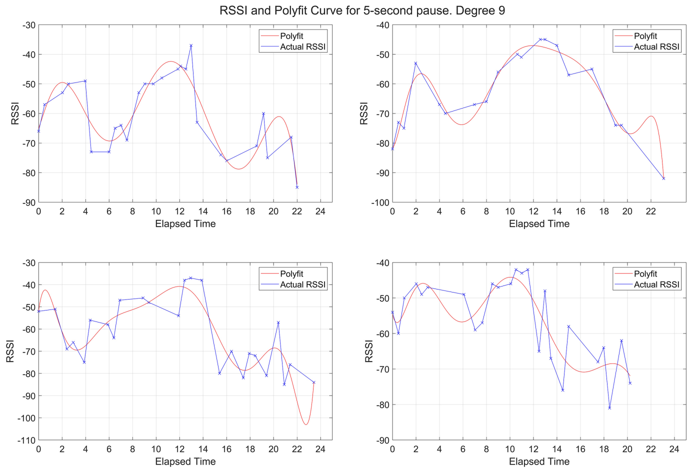


Fig. 3: Comparison of SSE of Varying Degrees of Polynomial for Curve Fitting

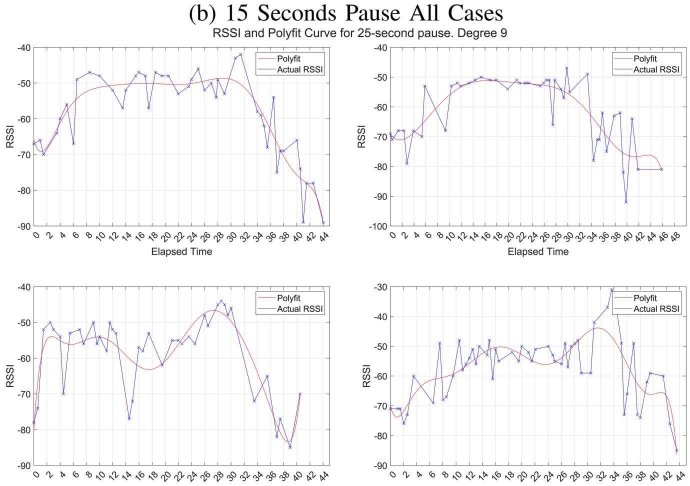
B. Sliding Window SD

Before diving into the discussion about sliding window SD, we must first consider whether the window should be based on time or number of samples. To understand this, we observe the Advertisements from the perspective of both the Broadcaster and the Observer. Through the lens of the Broadcaster, RSS values ensuing from Advertisements are regularly sampled time-series data as they are emitted at a fixed interval of 0.5 seconds. However, in its journey, these Advertisements are sometimes lost or delayed, resulting in irregularly-sampled time-series data from the Observer's point-of-view. If we see a graph of the RSS data as detected by the Observer without considering their time of detection at the top of the BLE stack, the RSS values would appear to be evenly distributed, therefore losing the important information about the gap in the



(a) 5 Seconds Pause All Cases

(b) 15 Seconds Pause All Cases



(c) 25 Seconds Pause All Cases

Fig. 4: Polynomial Curve Overlaid on the original RSSI

time of arrival of two consecutive RSSI. If the sliding window approach uses a sample-based window instead of a time-based one, it will consider the values that may be outside a trend in the overall RSSI if there are lost Advertisements in between. This is depicted in figure 5. Hence, to retain these nuances, we adopted a time-based windowing approach to draw inferences.

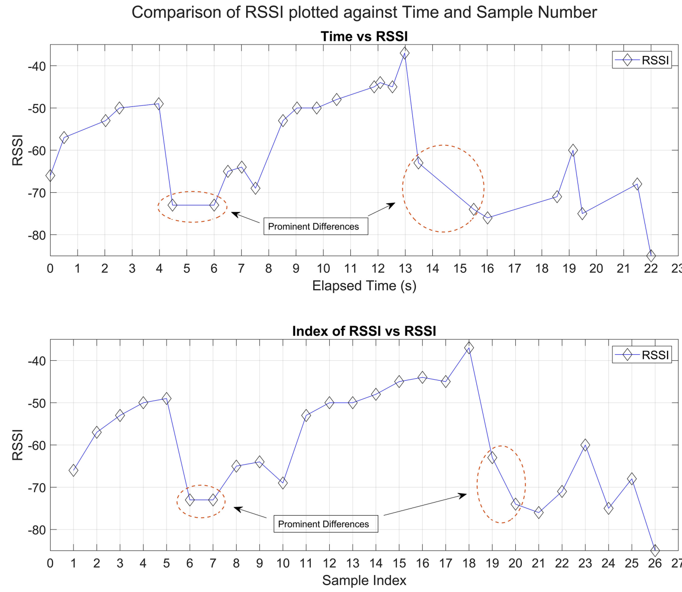


Fig. 5: Curve Fitting for Example RSS Values

Each of the 4 repetitions from every pause duration of 5, 15 and 25 seconds was subjected to the sliding window subset generation that varied between 2 and 10-second window sizes, totalling 108 data sets for the calculation of SD.

C. Pause Detection and Fine Tuning

As stated earlier, we expect flatness in the trend of RSS value during the pause which should be attributed to a smaller SD. We introduced an SD threshold parameter to be used with the obtained sets. This threshold parameter was identified by [32] by obtaining continuous RSS values for an extended period of time from a stationary pedestrian at the very location where our volunteer pedestrian pauses during the walks. For each case, we count the number of false positives and correct pause detection. However, we must further tune the obtained results to eliminate the chances of identifying isolated occurrences of below threshold SD values due to instances of anomalous data. And given the minimum pause duration studied in this work is 5 seconds, we only consider detected pause durations of over 4 seconds in length, that is 20% of the minimum pause duration. This 20% margin is chosen so that the delayed interception of stray signals from just before the volunteer pedestrian pauses that affect the emergence of flatness are addressed. A parallel coordinate plot for each case, in fig 6, shows our individual findings.

Accounting the total number of false positives and correct pause detection reveals that a window size of 9 provides an optimal balance between the two parameters of assessment. The relationship between false positives and correct pause detection against the window size is depicted in figure 7.

Finally, the graphs in figure 8 displays the outcome achieved by applying thresholding and the fine-tuning technique described in the Methodology section III to the sliding windowed

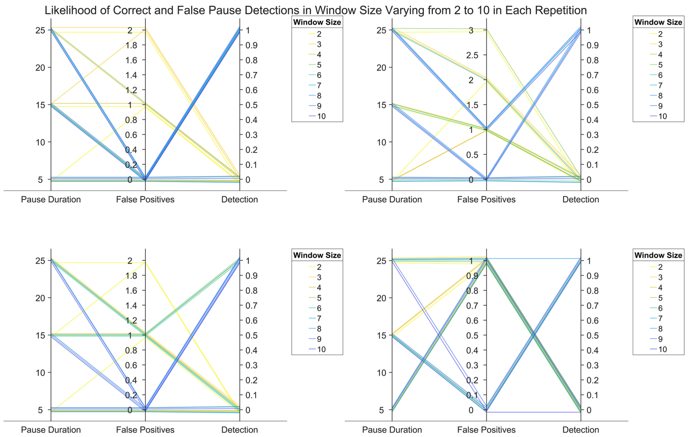


Fig. 6: Sliding window size efficacy through Parallel Coordinate Plot

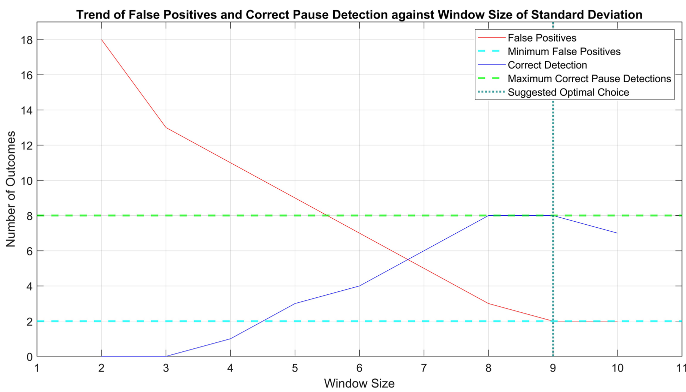
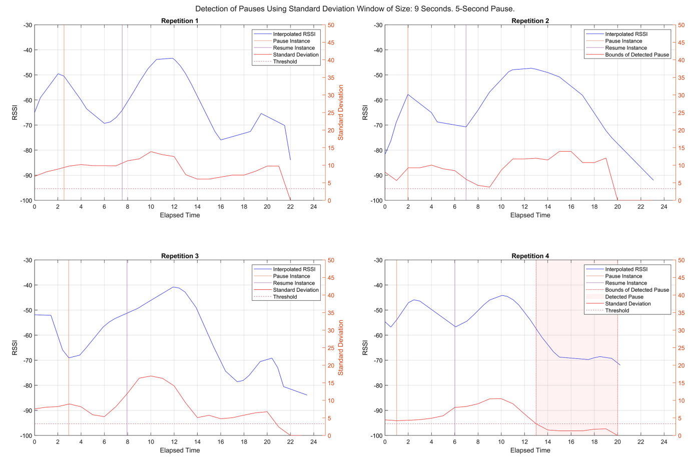
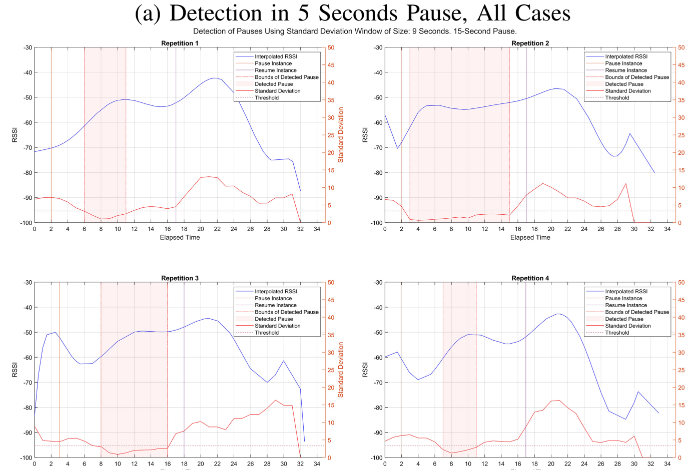


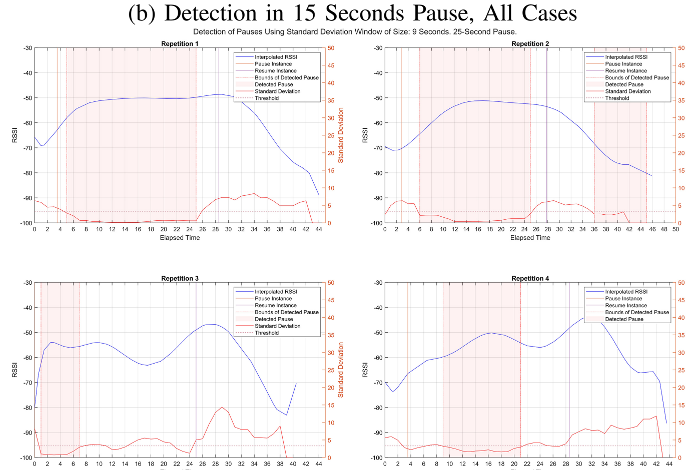
Fig. 7: Curve Fitting for Example RSS Values



(a) Detection in 5 Seconds Pause, All Cases



(b) Detection in 15 Seconds Pause, All Cases



(c) Detection in 25 Seconds Pause, All Cases

Fig. 8: Final Outcome of the Pause Detection Technique

SDs using a 9-second window on a degree-9 polynomial curve interpolation of the original RSS values to detect pauses.

V. Discussion, Conclusion and Future Directions

The final results show a strong indication of pause detection using only RSS values of a BLE Broadcaster. We had a total of 12 cases, 4 repetitions for each of 5, 15 and 25-second pauses. All of these cases were subjected to 9 different window sizes, varying from 2 to 10 seconds, to calculate the sliding SDs for the identification of a pause. With a window size of 9 seconds, we had the highest detection of a pause, in 8 out of 12 cases. For this window size, we also have the lowest number of false pause detections. It is essential to note that even if many patches of below threshold SD values are identified within the actual pause duration, we count it only as one, whereas, all the instances of false pause detection are added up in the final results. This means that as many false positive detections arising from even a single case are considered in the final results. This further emboldens our confidence in this approach since the false positive detection rate is very low.

It is also important to note that pause was not detected when the pedestrian stopped for 5 seconds. This could be due to the stray signals from before the pause overlapping the signals obtained during the pause. And since the fine-tuning rules out any pause length of less than 4 seconds long, it is difficult to identify a pause duration this low. For a 15-second pause, we had 100% pause detection and 0 false detections for a window size of both 8 and 9. We therefore recommend that such a system can detect a pause duration of 15 seconds and over, and at a macro level, may struggle to accurately detect pauses for a pause duration of fewer than 15 seconds.

The limitation of this approach is that there is no surety of pause identification, even at a greater pause duration. Also, using polynomial curve estimation is a technique that requires further investigation. Identifying the best fit in estimated curves require thorough research to prevent overfit and underfit, especially when the RSS values are obtained for an extended period. It should be emphasised that while a lower SSE indicates a better fit, closely aligning the curve to every data point may be ineffective in mitigating the effect of anomalous data on the RSSI trend. Additionally, the curves obtained through polynomial fitting consistently commence and conclude at the initial and final RSS values, respectively. Consequently, when there is a substantial time gap and a significant difference between the starting and ending RSS values and their adjacent RSS values, the resulting interpolated curve introduces artifacts that deviate from the actual trend exhibited by the RSS values as seen in the figure 4.

For future work, to identify if this technique is effective, data is being collected for pauses at different locations while travelling in both directions on the walkway. We are also interested in applying this technique when the Broadcaster is partially occluded. Additionally, the veracity of other statistical techniques such as *hurst exponents*, *sliding window median filtering*, *interquartile ranges*, and *convolution* applied in conjunction with the current technique can also be investigated.

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