In–Vehicle Positioning for Public Transit Using BLE Beacons

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Abstract

Public transit has been affected disproportionately by the social distancing requirements consequent to the COVID-19 pandemic. Technologies such as effortless ticketing and crowdedness assessment have the potential to increase safety and instill confidence for transit users. One key component of these technologies is the ability to detect the presence of a passenger inside a bus vehicle, as well as their approximate location within the vehicle. We present a preliminary study demonstrating the potential of a system that uses Bluetooth Low Energy (beacons), placed inside a vehicle, to localize a passenger within the length of the vehicle with an accuracy better than 1 meter. Based on these preliminary results, we are working on a long-term experiment that will collect RSSI data from BLE beacons (as well as GPS and inertial data) from passengers using the transit system of our campus.

Keywords

Effortless ticketing, crowdedness monitoring, Bluetooth Low Energy, positioning, public transit

1. Introduction

The COVID-19 pandemic has affected virtually all enterprises in the private and public sector. In particular, public transit has suffered disproportionally from loss of ridership [1, 2]. As a consequences of shelter-in-place ordinances, and with remote working becoming accepted and even encouraged in many lines of business, the commuting needs of many habitual bus or train riders have radically reduced. In order to enforce social distancing, transit operators have been forced to dramatically reduce the capacity of vehicles. Many potential riders are choosing not to use public transit for fear of contagion, even though there is scant evidence that, with appropriate precautions in place, transit poses serious risks of coronavirus outbreaks [3].

Yet, many people (in particular, essential workers who cannot afford private transportation) are still riding busses and trains. And once the pandemic will be under control, it is expected that ridership will increase again. Indeed, public transit has a critical role for sustainable, affordable, and accessible mobility [4]. Even in the era of autonomous vehicles, mass transit will be necessary to manage traffic congestion [5]. In the words of Jeff Tumlin, Director of Transportation at San Francisco Municipal Transportation Agency (SFMTA): "Transit remains the most energy and space efficient way to move large numbers of people over long distances in and around cities" [6].

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However, transit riders in the post-pandemic world will have increased expectations. Prophylactic measures, such as maintaining social distancing and avoiding touching surface in common places, are likely to remain on the mind of travelers. Agencies will need to put policies and infrastructure in place that make riders feel safe and comfortable while using public transit [7, 8].

This contribution describes work in progress on a project that addresses two interconnected services contributing to a safe travel experience: *effortless ticketing* and *crowdedness monitoring*. By effortless (or implicit [9]) ticketing, we mean methods that enable payment of the correct fare as triggered by the mere presence of the user inside the vehicle. Current touchless fare payment technology still requires travelers to approach a near-field communication (NFC) reader or possibly a QR reader [10] located in the vehicle. This creates "accumulation points" of social proximity, which may slow the flow of passengers entering the vehicle and thus increase boarding times. Increasingly, agencies are offering the possibility to purchase tickets through an app (e.g., Transit, or Google Maps). Although this obviates crowding near card readers in the vehicle, it requires travelers to identify the correct fare (e.g., if the cost depends on the fare zones traversed), or to input the intended route in the app. A real effortless ticketing system would not require the users to take any actions, except for starting an app in their smartphone. It would automatically identify the vehicle boarded by the passenger (Be In/Be Out, or BIBO, modality [9]), and charge the correct fare. Users would not need to input information such as their itinerary or the specific bus or train line they are going to use. Upon boarding the bus vehicle or train car, the user would receive a notification (e.g., via a vibration) from the system that the vehicle has been identified, and that that ticketing is taken care of.

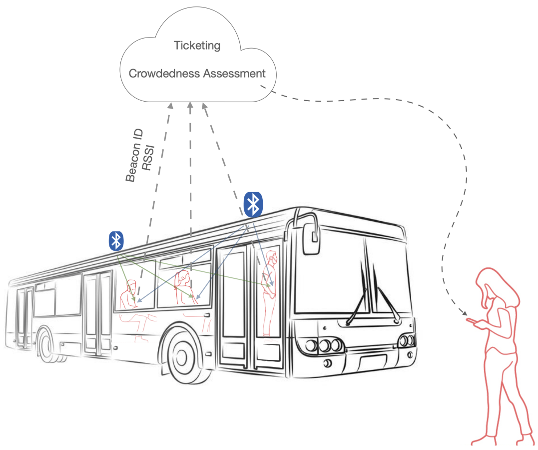

Figure 1: Our envisioned system uses RSSI data recorded from the in-vehicle BLE beacons for passenger positioning, enabling effortless fare payment and crowdedness assessment.

The same mechanism that enables effortless ticketing can be used to assessing and track the distribution of passengers in a vehicle. Crowdedness monitoring has received increased recent attention [11]. We envision a system that measures not only the approximate number of passengers, but also their spatial distribution in the vehicle. This could be very useful when deciding which door to enter a vehicle from. For example, if riders in a train cart or bus vehicle are concentrated in the front half, a passenger waiting at the stop may decide to enter from the back door (see Fig. 1). This information could also be very valuable for transit agencies, which can put in place provisions to ensure a uniform distribution of passengers in their vehicles. A few transit apps provide this occupancy information (when available) to passengers awaiting at a bus stop. Passengers can then choose, based on this information, whether to board the upcoming vehicle, or, if they determine that the vehicle is too crowded for their comfort level, wait for the next one, or use a different means of transportation. Crowdedness can be measured using specialized sensors (e.g., seat sensors or cameras), or through crowdsourcing [12, 13]. Occupancy sensors, however, are generally expensive, involve some form of vehicle retrofitting, entail maintenance costs, and typically require an additional data communication channel. Crowdsourcing approaches are attractive because they require no instrumentation, but they depend on the willingness of passengers to input data during a trip. It has been observed that contributors to crowdsourcing projects (e.g., OpenStreetMap) tend to belong to the more affluent and educated portion of the society [14], which may not be representative of large swaths of the population riding public transit.

We propose to use Bluetooth Low Energy (BLE) beacons as the underlying technology for both services considered (effortless ticketing and crowdedness monitoring). BLE beacons are inexpensive and unobtrusive. Battery operated models (e.g., Kontakt Tough Beacon TB18-2) can last up to 80 months on a battery charge, and require no vehicle retrofitting (including wiring) nor maintenance during this period. These factors are critically important, given the tremendous budget constraints that agencies are experiencing due to recent loss of ridership.

Our concept is very simple. Passengers start an app on their phone; once they board the bus, light rail, or train vehicle, the app detects the ID of the onboard BLE beacons, as well as the Received Signal Strength Indicator (RSSI) from each beacon. This information is transmitted (by the user's phone) to a cloud server, which is cognizant of the association between beacon ID and specific trip in the agency's General Transit Feed Specification (GTFS) table [15]. The system can then charge the user the appropriate fare, and also (based on the received RSSI), determine the location of the user in the vehicle. By aggregating information from multiple users in the same vehicle, a measure of crowdedness and of its spatial distribution is generated, which can be advertised through standard mechanism, such as GTFS Real Time [16], for other online transit services or apps to be picked up.

In this contribution, we present results from a preliminary study on passenger localization within a bus vehicle using BLE beacons. We instrumented a campus shuttle bus with four BLE beacons, and conducted multiple data collection session. RSSI data was collected from all beacons while the experimenter sat in different location within the vehicle. Analysis of this data confirms that localization accuracy of up to 1 meter (along the length of the bus) can be achieved using BLE beacons in realistic conditions.

2. Related Work

The potential of BLE beacons for effortless/implicit ticketing using the BIBO paradigm was first demonstrated by Narzt and colleagues in 2015 [9]. In their prototype, the passengers' smartphones were tasked with sending (via BLE) an ID that was received and processed by a system within the vehicle. This approach, however, requires some level of retrofitting (including wiring and Internet connectivity) that may discourage adoption by cash-strapped agencies. The system recently proposed by Ferreira et al. [17] (developed through a participatory co-design cycle involving potential customers [18]) is closer to our envisioned BLE beacon placement scenario. This system, however, was only tested with a single beacon placed in one bus vehicle.

While BLE beacons, as well as NFC or QR code readers, can be used to monitor the presence of passengers in a vehicle, other mechanisms have been explored that don't require such sensors. For example, by matching the GPS tracks [19] or the time series from inertial or barometric sensors collected by the user's smartphones [20, 21, 22] with those recorded by a sensor in the bus vehicle, it is possible to determine whether the user is on a certain bus route. However, GPS-denied environments, or spurious motion of the smartphone, can generate errors. None of these methods can provide information about the location of the user in the vehicle, which is necessary to compute the spatial distribution of passengers.

The use of BLE beacons for localization has been well studied. In ideal conditions, power decay models [23] could be used in a multilateration scheme to precisely compute the location of the receiver (the user's smartphone). In practice, researchers have found that power decay models cannot be relied on, due to a multiplicity of reasons including multi-path fading and variations in time of the signal power [24]. The standard approach is based on fingerprinting [25], whereby RSSI data is collected from a dense set of known locations, and the user's location is then regressed from the received RSSI vector.

3. In–Vehicle Positioning

The goal of this study was to assess the performance of a positioning system based on the RSSI from multiple BLE beacons placed in a bus vehicle. Note that various factors could complicate the location inference problem, such as multiple reflections, occlusions by obstacles (e.g. the seat backs) or other passengers, as well as self-occlusions (e.g., the user keeping the smartphone tucked in a pocket.) In order to ascertain whether localization in a bus vehicle is even possible with data from BLE beacons, we conducted several data collection sessions in a campus shuttle bus. The vehicle (8.3 meters long, 2.6 meters wide) was equipped with four Kontakt Tough TB15-1 BLE beacons, configured as iBeacons with an advertisement interval of 350 ms (see Fig. 2.) We created an iPhone app that collects timestamped RSSI data from the different beacons. During each data collection session, an experimenter sat on different seats as the vehicle drove through its regular route, while collecting data from the BLE beacons using either an iPhone 7 or an iPhone 8. At each seat, the experimenter first recorded data for two minutes while holding the phone in their hand, then for two minutes while keeping the phone in their front pant pocket. The vehicle was empty for most of the time, except for a few occasional passengers (at most three passengers besides the experimenter at a time).

We first ran three data collection sessions with the BLE beacons set to Power level 1. With this setting, the RSSI at 1 meter of distance is of -84 dBm, and the nominal range is of approximately 4 meters. We then conducted one session at Power level set to 2 (RSSI of -81dBm at 1 meter, nominal range of approximately 10 meters). Figs. 3 and 4 show the layout of the beacons in the bus, as well as the seats considered for data collection for each power level. This data set was used to ascertain whether it would be possible to estimate, based on the RSSI received from different beacons, the location of a user across the length of the bus (i.e., to determine, at least approximately, the seat row in which the user was positioned.) We did not attempt to estimate the user's position across the width of the vehicle, given the vehicle's relatively narrow geometry.

The RSSI collected at each seat, averaged over time, over the two phone placements (in hand and in pocket), and, for the case of Power level 1, over the three sessions, is presented in the top plot of the figures. In this plot, the horizontal axis represents the seat row position along the length of the bus. For each seat, we show the average RSSI received from each BLE beacon. As expected, the RSSI from beacon B1 (in front of the vehicle) was generally higher for seats in the front half of the vehicle. The opposite behavior can be observed for the data received from beacon B4, at the back of the vehicle. The RSSI data collected from B2 and B3 had a less clear dependence on the seat location. Interestingly, signal was received even at seats that were at about 7 meters of distance from a beacon even when the BLE power level was set to 1 (with a nominal 4 meter range). This is likely due to reflection from the metallic surfaces of the vehicle.

To verify whether the vector of RSSI data collected from the different beacons could be used to accurately measure the seat row location of the user, we trained a simple linear predictor of seat row position from data collected in half of the seats (shown with a dark contour in the figures.) We then used this predictor to estimate the row location of the remaining seats, based on the recorded average RSSI data. The results are shown in the lower row of Figs. 3 and 4, with seat identified by their color. Using data collected from all four beacons, the root mean square error (RMSE) of estimated row position was of 0.57 meters (max error: 1.1 m) when using Power level 1, and of 0.33 meters using Power level 2 (max error: 0.62 meters).

As noted earlier, the plot of the RSSI values in Figs. 3 and 4 suggests that while data from beacons B1 and B4 clearly correlates with the seat row location, the remaining beacons appear to be less informative. Based on this observation, we repeated the same test, but only considering RSSI data collected from B1 and B4. In this case, the RMSE of estimated row position was of 0.50 meters (max error: 0.93 m) when using Power level 1, and 0.30 meters using Power level 2

Figure 2: Example of placement of a BLE beacon (Kontakt Tough TB15-1) on the ceiling of the shuttle bus.

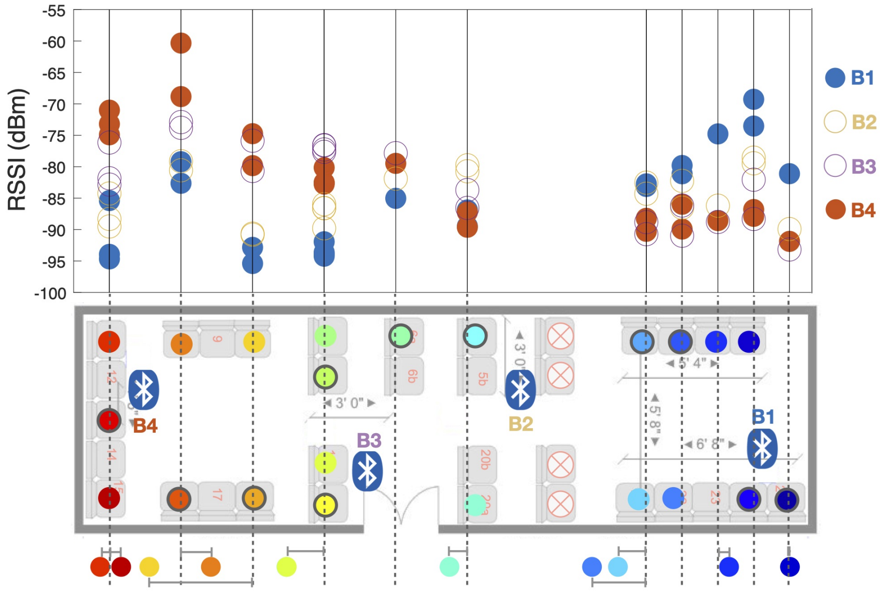

Figure 3: Layout of BLE beacons in shuttle bus (the front of the vehicle is to the right of the figure.) The seats from which RSSI data was collected are marked with distinctive colors. The linear prediction model was trained from data collected at the seats marked by a dark contour. The average RSSI values received at each seat are displayed in the top plot for each BLE beacon. The horizontal axis represents the seat row location along the length of the bus. The bottom row shows the seat row location estimated from RSSI data using our linear predictor (only seats that were not used in training are shown.) Errors (estimated vs. actual seat row location) are shown by gray segments. The power level of the BLE beacons was set to 1.

(max error: 0.66 meters).

From this preliminary analysis, we can draw the following observations:

1. Localization of a passenger within the length of the bus vehicle is possible using BLE beacons, to at least 1 meter accuracy. This information could be used to derive a coarse–scale crowdedness index. For example, one could divide the length of the bus into 3 or 4 section, and count the number of passengers in each section (where, as in the system envisioned in Sec. 1, the RSSI data would be transmitted from the users' phones to a cloud server, e.g. as part of an effortless payment app.)
2. Setting the beacons at power level 2 appears to produce better localization accuracy. It should be noted, though, that a higher transmission power directly affects the lifetime of the beacon when battery operated. The trade-off between accuracy and system lifetime needs to be carefully considered when designing a real-world BLE beacons system.
3. Using two beacons (one in front of the bus, and one in the back) appears to give similar (or better) results than using data from four beacons, distributed along the length of the bus. This somewhat surprising results suggests that data from beacons B2 and B3, which were placed in the middle of the bus, contributed little (and possibly noisy) information for the purpose of positioning.

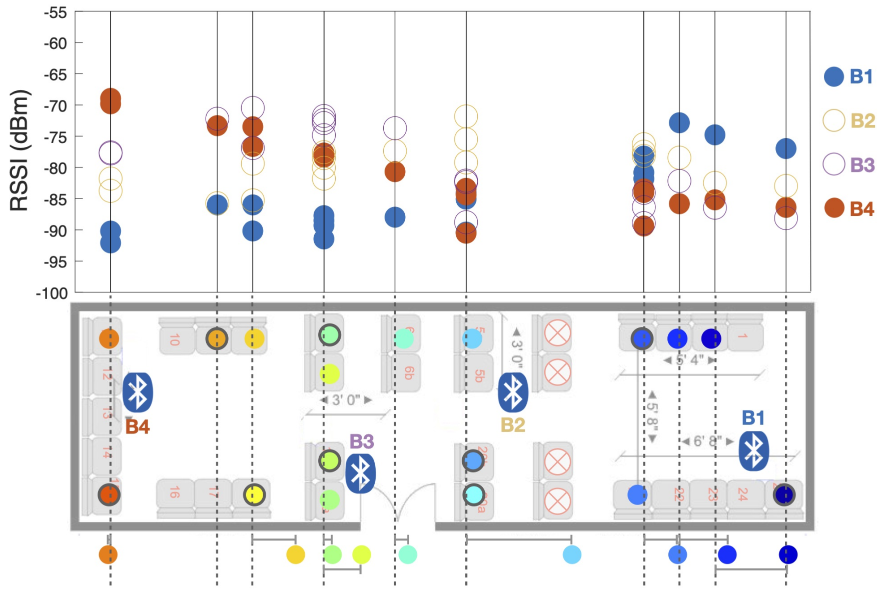

Figure 4: See caption of Fig. 3. The power level of the BLE beacons was set to 2.

4. Discussion and Future Work

The data collection and analysis described in the previous section has shown promising results for the use of BLE beacons in measuring the position of a passenger along the length of the vehicle. However, more research work is needed to obtain a system that is robust and reliable in the face of multiple adversarial situations. For example, while the radio signal from one or multiple beacons can almost certainly be detected once one has boarded the vehicle, the same signal could potentially be detected also outside the vehicle. This could create false alarms, for example when a passenger is waiting at a stop, and a bus or train the passenger is not planning to board is coasting to the stop. These situations could be managed by looking at the time series of RSSI measurements, possibly combined with information from the inertial sensors in the user's smartphone. For example, if the sensors detect that the user is moving of motion that is consistent with that of a vehicle [26], and connection with the beacons remains stable, it could be safely assumed that the user has boarded the departed bus. Although a similar result could be obtained by matching the GPS track of the user's smartphone with that of the bus, although this would not be an option in a GPS-denied environment (e.g., in a subway).

Another situation that could potentially generate errors is one with multiple bus vehicles arriving at the stop at the same time. In this case, it could be possible that the user's smartphone, even after boarding, may receive radio signal from beacons in other nearby vehicles, potentially triggering an erroneous system response. Even in this case, joint analysis of inertial and RSSI measurements could break the ambiguity and assign the passenger to the correct vehicle.

Standard fingerprinting procedures are unlikely to produce reliable results unless confounding factors such as the presence of nearby travelers, whether the user is standing or sitting, and whether the user is holding the phone in their hand or tucked in a pocket, are taken into account. We believe that addressing the open problems mentioned above is only possible if a representative data set, collected in realistic situations, and adequately annotated, is made available. A number of open access data sets containing data from BLE beacons (for indoor localization applications; e.g., [27, 28]) or from inertial sensors (e.g., [29, 30, 31, 32]) already exist. However, none of these data sets would be representative of the situations considered here. What is needed is a collection of synchronized measurements of RSSI, inertial data, and GPS tracks, collected from passengers' smartphones, that could be analyzed viz-a-viz the known trajectory of the transit vehicle that was boarded by these users. This data must be recorded by multiple different users, using different types of smartphones, and in various different conditions (location in the vehicle, crowdedness level, atmospheric conditions). We are in the planning phase of a new, extensive data collection, with data crowdsourced from the students using the campus shuttle of our university.

5. Conclusion

We have presented results from a preliminary study of a system that can localize passengers in a bus vehicle from the RSSI signal received from multiple BLE beacons placed in the vehicle. In spite of the non-ideal conditions of this environment (with multiple reflections and occlusions), a simple linear predictor was shown to produce better than 1 meter accuracy. This simple experiment suggests that coarse-scale localization within the length of the bus is possible using BLE beacons. This localization system could be used in the context of effortless ticketing and crowdedness assessment applications. We are planning a large-scale data collection study in realistic conditions, to verify whether the promising results presented in this contribution scale up in real-world public transit applications.

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