Review- "BLED One Touch Information"

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Abstract

Proximity based services (PBS) require high precision detection, energy efficiency, wide range of recepti on, low cost and availability. Most of the existing technologies,

however, can not meet those requirements. Apple's Low Energy Bluetooth (BLE), called onecandidate during this domain and has become an almost industry standard for PBS. However, due to its various limitation, it suffers from poor accuracy in proximity detectionReceived Signal Strength Indicator (RSSI) to enhance proximity detection accuracy of BLE device, we present two algorithms that address the inherent flaws in BLE Beacon's current proximity detection approach. Our first algorithm, sever side running average (SRA), uses the pathlossmodel based estimated distance for proximity classification. Our second, extreme Kalman Filter (SKF) algorithm, uses Kalman Filter together with SRA, ourexperimental result show that SRA and SKF perform better than the present moving average approach utilized by BLE Beacon. SRA ends up in a couple of 29% improvement while SKF ends up in a couple of 32% improvement over the present approach in proximity detection accuracy.

Index terms Location BasedServices, BLE device, Internet of Things, Proximity Detection, Kalman Filter.

Introduction

Location based services (LBS) are services provided to users supported their location. Such services require either identifying the user's exact location, referred to as micro location, or obtaining a rough estimate of the user's distance to a particular Pointof Interest (POI) referred to as proximity-based services (PBS). The fundamental requirements of PBS are high proximity accuracy, energy efficiency, wide reception range, low cost and availability. For PBS, the estimation error of user's proximity to the POI must be limited within certain bounds, preferably within 1meter [1].Different technologies are used for Proximity detection including Wi-Fi [2], Radio frequency identification devices (RFIDs)[3], and ultrawideband (UWB). however, these technologies don't seem to be primarily intended for PBS and don't fulfill the aforementioned requirements.

Bluetooth Low Energy (BLE) is a viable technology for PBS. While different BLE- based solutions are available for PBS [4], reliable solution requires modifying the BLE stack to accommodate proximity specific protocols and optimization that are currently not part of BLE. Google's Eddystone and apple's BLE Beacon are two such widely used protocols that are based on BLE and optimized to provide PBS. OUR paper focuses on BLE Beacon protocol as it is industry standard for PBS [5], but our algorithm can also be used with Eddystone based system. The BLE devices using BLE Beacon protocol are also called BLE Beacon or beacons. BLE Beacon periodically transmit a Universally Unique Identifier (UUID) that is picked up by the user's mobile device.Oncethe user device obtains a UUID, it contacts a server to inquire about the UUID and therefore the event related to the BLE Beacon. The server responds back with

relevant information and might trigger a happening like responding back to the user with a reduction coupon opening a security door supported the user's proximity to the door. Figure 1 shows the working rule of the BLE Beacon. Since energy efficient and long range BLE is on the market in modern smart phones, BLE Beacon would be feasible for PBS if the proximity detection accuracy may be improved to satisfy the necessities for PBS. In BLE Beacon based systems, the strength of the received signal (from BLE Beacon) at the user device is employed as an estimate of how close the user device is employed as an estimate of how close the user is to the beacons. The proximity of the user of the beacon is categorized into any of the four zones provided in table different application may theoretically be used to supply PBS to any of the above listed zones. Its therefore fundamental to accurately compute the user's proximity to the BLE Beacon. A customer who enters a store like 'Starbucks' and is within the counter's immediate region, may avoid long queues by exploiting its precise proximity to the BLE Beacon. The user can confirm the order through his smartphone and get hold of the order supported his proximity. Such service is just possible with accurate proximity estimation and therefor the proximity error being within certain bonds. Because PBS are primarily provided in indoor environments that are at risk of noise because of the presence of obstruction, apple's core location framework reports a moving average of RSSI values received from beacons to scale back fluctuation. However, the moving overaged RSSI values fluctuate drastically because of noise and can't consequently produce an accurate estimate of the particular distance. Therefore, the estimated proximity will be erroneous and not suitable for PBS, another inherent flaws in BLE Beacon's current proximity detection approach is that the users are classified into different zones supported specific RSSI values, i.e. its assumed that each one the indoor environments behave identically, but this is often unrealistic and further deteriorates the performance of beacon based PBS to enhance the detection accuracy of the BLE Beacon-based proximity services, we developed two new server-based algorithm that incorporate moving average and Kalman filter to enhance the proximity detection accuracy of an BLE Beacon based system we propose to average the computation power of the server, and not the device, for running the algorithms to scale back the energy consumption of user device, and to use the greater computing power of servers.

Literature Survey

Related work Kumar et al, [6] presented an internal localization system called uricase that emulates large antenna arrays on user devices through a completely unique formulation of synthetic Aperture Radar (SAR). Uricase is micro location and

proximity-based services, however the energy consumption of the uricase location is high and requires its users to rotate their devices for location purposes [6]. Furthermore, the user device must have a minimum of two antennas to emulate large antenna arrays.

Zone	Distance	Table I: The classification of proximity zones based on distance between the user and the BLE Beacon.
Immediate	<1 m	
Near	1-3 m	
Far	>3 m	
Unknown	Device not ranged	

Klokmoseet al. [2] proposed a Wi-Fi proximity detection system for mobile web application that is based on proximity adaptive HTTP responses. Despite its low cost, this approach can only offer proximity based services if the consumer interface is generating traffic [2]. Furthermore, Wi-Fi also lacks the required accuracy for proximity detection as describe by Ghose [7] and isn't energy efficient bolicet al required accuracy

required for proximity detection asdescribed by Ghose [7], and isn't energy efficient. Bolic et al [3] proposed a completely unique RFID device called "sense-a-tag" (ST) for detecting and decoding backscatter signals fromdifferent tags in its vicinity. The proposed ST is incorporated in a very standard RFID system to enhance proximity detection accuracy for IOT. However, the range of RFIDs may be a major challenge particularly in large spaces. Ghose et al. [7] proposed a mobile for proximity detection a brand-new path-loss model that takes the mobile orientation under consideration to enhance the system performance is described in [7]. The drawbacks of those technologies is that they're not primarily focused on accurate and energy efficient PBS. In contrast, BLE Beacon technology is more fitted to proximity detection. In our prior work [8], we used BLE Beacon to produce indoor localization to produce indoor localization services to any user. We used particle filtering to trace the placement of a user with a localization error as low as 0.97 meters. During this paper, we describe two novel server-based proximity detection algorithm that respectively leverage moving average and Kalman filter to enhance the accuracy of an BLE Beacon based proximity detection system. To the simplest of our knowledge, this can be the first try to improve the proximity detection accuracy of BLE Beacon using Kalman filters.

Our first algorithm, the server side running average (SRA), suitable for environments with less interference noise (in less crowded place like coffee shops or commissary with fewer Wi-Fi



Figure 1: Working Principle of the BLE Beacon.



access points (AP)), improves the proximity detection accuracy of BLE Beacon by 29% compared with this moving average based approach used today by apple's core location framework. Our second algorithm, server side Kalman filter (SKF), is suitable for big spaces with greater interference noise (typically in additional crowded space with the next number of Wi-Fi APs) and could be a modified version of SRA, improves proximity detection accuracy by 32% over apple's current approach we've open sourced the aforementioned algorithms together with an end to finish micro-location framework1 to solicit feedback, and to enable collaboration and contribution from the research and company community. The paper is structured as follows: section 2 discusses related work. Section 3 describes our proposed server based algorithm section. Section 4 present our experimental setup and obtained result. Section 5 present a close discussion of our obtained result section 6 present our conclusion PBS are primarily provided in indoor environments that are susceptible to noise thanks to the presence of obstruction. Apple's core location framework reports a moving average of RSSI values received from beacons to scale back fluctuation. However, the moving averaged RSSI values fluctuate drastically thanks to noise and can't consequently produce an accurate estimate of the particular distance. Therefore, the estimated proximity may be erroneous and not suitable for PBS. Another inherent flaws in BLE Beacon's current proximity detection approach is that the users are classified into different zones supported specific RSSI values, that is its assumed that each one the indoor environments behave identically, but this is often unrealistic and further deteriorates the performance of beacon-based PBS. To improve the detection accuracy of the BLE Beacon based proximity services, we developed two new server-based algorithm that incorporate moving average and Kalman filter to boost the proximity detection accuracy of an BLE Beacon based system. We propose to leverage the computational power of the server, and not the device, for running the algorithms to cut back the energy consumption of user device, and to take advantage of the greater computing power of servers. Our first algorithm, the server side running average(SRA), suitable for environments with less interference noise (in less crowded places like coffee shops or

ISSN: 2233-7857 IJFGCN Copyright ©2020 SERSC commissary with fewer Wi-Fi access points (AP)), improves the proximity detection accuracy of BLE Beacon by 29% in comparison with the present moving average based approach used today by apple's core location framework. Our second algorithm, server side Kalman filter (SKF), is suitable for big spaces with greater interference noise (typically in additional crowded space with a better number of Wi-Fi Aps) and may be a modified version of SRA, may be a modified version of SRA, improves proximity detection accuracy by 32% over apple's current approach. We've open sourced the aforementioned algorithms together with n end to finish micro location framework1 to solicit feedback, and to enable collaborations and contribution from the research and company community. The paper is structured as follows: section 1 discusses related work. Section 2 discusses related work section 3 describes our proposed server-based algorithms. Section 4 presents our experimental setup and obtained result. Section5 presents an in-depth discussion of our obtained result. Section6 presents our conclusion.

Conclusions

Proximity based services (PBS) can be leveraged in different locations including airports, retail stores, hospitals and stadium etc. however, the current technologies can'tfulfill the accuracy, energy consumption, range, cost and availability requirements for PBS. BLE Beacon, the industry standard for PBS, currently lack the accuracy to be utilized for efficient and accurate PBS. In this paper, we proposed two server-based algorithm that improved the proximity detection accuracy of an BLE Beacon based proximity solution by handling the inherent limitations of the current approach utilized by apple for proximity classification. We used the current approach as a benchmark that resulted in proximity as a benchmark that result in proximity classification.

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