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Short Paper: Towards Low-Cost Indoor Localization using Edge Computing Resources

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***Abstract*—Emerging smart services, such as indoor smart parking or patient monitoring and tracking in hospitals, incur a significant technical roadblock stemming primarily from a lack of cost-effective and easily deployable localization framework that impedes their widespread deployment. To address this concern, in this paper we present a low-cost, indoor localization and navigation system, which performs continuous and real-time processing of Bluetooth Low Energy (BLE) and IEEE 802.15.4a compliant Ultra-wideband(UWB) sensor data to localize and navigate the concerned entity to its desired location. Our approach depends upon fusing the two feature sets, using the UWB to calibrate the BLE localization mechanism.**

I. Introduction

A significant technical roadblock that impedes the widespread deployment of smart applications such as smart parking, patient monitoring and indoor navigation systems, stems from a lack of an inexpensive entity localization solution. Existing localization solutions are either too costly (e.g. LIDAR, imaging sensors, radar), or incur high installation costs, requiring power and communications wiring for a large number of sensors. To address this limitation, in this paper we present our low-cost indoor localization and navigation system, which performs continuous and real-time processing of Bluetooth Low Energy (BLE) and IEEE 802.15.4a compliant Ultra-wideband(UWB) sensor data on low-cost edge devices.

The approach we propose in this paper is to combine the two modalities, i.e., BLE Received Signal Strength Intensity (RSSI) fingerprinting and UWB RF positioning using a computation architecture that allows us to fuse this information in real-time. We expect that frequent visitors, e.g. drivers with permits, parking patrol vehicles, nurses in hospitals, will be equipped with both UWB tags and BLE-enabled Android devices, and contribute to building and maintaining the RSSI fingerprint map. For entities without UWB tags, we rely on indoor positioning by BLE RSSI fingerprint matching. Since RSSI fingerprint maps go “stale” quickly due to fast fading of the BLE channel characteristics, we rely on such dual-modality-equipped frequent occupants of these indoor spaces to keep the fingerprint map up-to-date. Streaming all the sensor data to the cloud for processing will incur a prohibitively large latency which is highly undesirable for these applications. Hence, we have used Intel Edsion boards as low-cost edge devices to process the sensor data at the edge (near the source of data). This is the key concept behind Fog Computing [1] and Mobile-Edge [2] computing paradigms.

Our approach is supported by prior research which suggests that fingerprint based localization using WiFi [3], [4], [5], [6], [7] or IEEE 802.15.4 compliant radios [8], [9] can yield an average positioning accuracy under 3m. However, it has been observed that BLE is substantially more susceptible to fast fading than IEEE 802.15.4 or WiFi [10], since BLE beaconing operates on a much narrower, 2 MHz wide channel as opposed to the 22 MHz wide channel used by WiFi and 5 MHz wide channel used by 15.4. Hence, our solution also relies on the more accurate Ultra-wideband (UWB) Radio Frequency (RF) time-of-flight based ranging and positioning as the ground-truth for periodically updating the fast-fading BLE RSSI fingerprints. UWB is another indoor localization technology that has reached maturation and has broken a low price point (e.g., transceivers from vendors such as Decawave [11] are available in the sub-$10 range). Decimeter-scale accuracy has been reported indoors with direct line of sight between UWB beacons and a wireless tag which is to be localized. However, since these UWB radios are not in current handheld devices, this technology alone is not sufficient for indoor localization that can be used by general public.

A. Related Work

A wealth of research work exists in the field of indoor localization. Broadly, approaches for indoor localization can be categorized into: angle-based, fingerprinting-based and ranging-based solutions [12]. Angle-based approaches require expensive and specialized directional antenna which is unsuitable for widespread adoption [12]. Fingerprining [13] and Radio RSSI (Wifi, Bluetooth, ZigBee) based solutions [14], [15], [16], [17] are the least expensive solutions, requiring no specialized hardware, which makes them amenable for a wide variety of consumer applications. Prior efforts [17], [18], have explored the BLE transmission model, i.e., reception probabilities at varying distances even in the presence of obstruction, and have successfully demostrated the use of BLE for localization.

Although, RSSI-based methods are easily accessible, they are less-accurate and require prior-site information, cost-intensive fingerprinting and continuous updating to accomodate time varying channel characterisitcs. Similar to previous efforts which rely on crowd-sourcing [19], [20], we rely on frequent visitors like patrol vehicles in a parking garage, to keep the fingerprints up-to-date. Time-of-arrival (TOA) based ranging methods, such as UWB ranging [21], are much more robust and accurate. However, UWB technology is still under development and is not available on current handheld devices.

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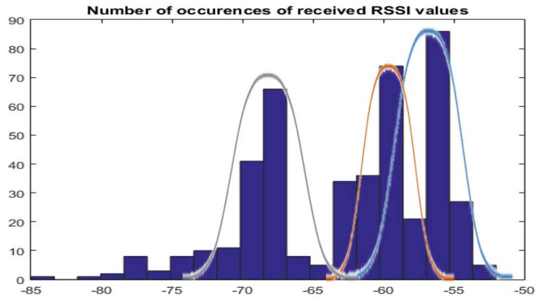

Fig. 1. A representative histogram of RSSI values received from a beacon. The three peaks correspond to the mean RSSI value received on each of the three advertising channels. Though the association between beacon messages and the corresponding channels is not available through the Android BLE API, by modeling the histogram as a mixture of three Gaussian kernels, the mean and variance of the RSSI values can be estimated on a per-channel basis.

Hence, our solution combines low-accuracy, easily-accessible BLE RSSI fingerprintng with high-accuracy UWB ranging.

II. RSSI Fingerprinting

BLE operates on a 2.4GHz ISM band which is divided into forty 2 MHz wide channels. Out of these 40 BLE channels, three are dedicated as advertising channels, and the rest are used for data exchange. BLE beacons are a special class of BLE devices which are limited to BLE transmission-only functionality and use the BLE advertising channels for periodic beaconing. However, we found that the BLE channel number of the incoming beacons is not exposed through any of the Android APIs, which makes RSSI fingerprinting-based localization challenging with Android devices.

Hence, we model the RSSI value of a beacon on a given BLE advertising channel as a Gaussian random variable. Therefore, as shown in Figure 1, the set of received RSSI values from a given beacon can be treated as a mixture of three Gaussians (one for each advertising channel). Collecting a sufficient number of RSSI observations at a given position allows us to characterize the empirical distribution of the received RSSI values. Intuitively, the measured distribution (i.e., the position and magnitude of peaks, etc.) will be characteristic of the given position, and will be sufficiently different even if the position changes by as little as a meter. Furthermore, by increasing the number of BLE beacon devices, we expect that the efficiency of distinguishing positions by BLE RSSI fingerprints will increase, as more data is available from a spatially diverse set of beacons.

Ideally, we would like the fingerprint map to remember the shape of each beacon's empirical RSSI histogram at each grid point of the discretized coverage area. Storing the actual histograms, however, is not beneficial as it would have an unnecessarily large memory footprint. Moreover, the empirical histograms often contain transient peaks that are artifacts of fast fading, and capturing these would adversely affect localization accuracy. Hence, we have devised two methods for representing RSSI fingerprints: Expectation Maximization (EM) and Tercile-based methods.

In the EM-based method, we use the Expectation Maximization algorithm to find the parameters $< prior, \mu, \sigma >$ for each of the three Gaussian kernel components, where $prior$ is the weight of the kernel, μ and σ are the mean and standard deviation, respectively. If there are N BLE beacon devices deployed in the system, the fingerprint map for each grid position will comprise N, 9-field long vectors.

Since the EM algorithm is computationally expensive, and may not be suitable for devices with power or computational constraints (our Edison Nodes), we devised a lightweight fingerprinting solution relying on finding the terciles of the empirical RSSI distributions. Assuming that a beacon transmits equal number of messages on all three channels and that the standard deviation of the RSSI values is the same for each channel, the lowest third of the received RSSI values will correspond to the beacons received on the channel that has the highest path loss of the three. Similarly, the highest third will correspond to the channel with the lowest path loss, leaving the middle third coming on the third channel. Therefore, we use the medians of these three parts, i.e., the 1st 6-quantile, the 3rd 6-quantile (which is the median of the entire population), and the 5th 6-quantile as fingerprints. The tercile-based approach yields $3N$-long feature vectors per grid position, where N is the number of beacons. The tercile-based approach trades off computational efficiency for accuracy. Unlike EM, this technique does not capture the variance of the RSSI values nor does it adapt to scenarios when the number of beacon messages received on different advertising channels is asymmetric.

For localization, it is sufficient to compare the Euclidean norm (L_2 distance) of the feature vectors of the target entity's unknown position with the precomputed feature vectors of all grid positions, and return the grid position for which the L_2 distance is the smallest. Our experiment results show that Tercile-based localization has sub-milisecond latency and comparable performance with the more expensive EM-based localization, hence it is well suited for real-time indoor localization and navigation.

III. Implementation and Experimental Setup

We implemented our ideas and conducted a number of experiments to validate our claims. One of these experiments, reported in this paper was performed in a 6.4x5.5 meter area which was divided into a logical grid composed of 1x1 meter grid-cells. In this experiment, an Intel Nuc (with 1.6GHz Intel Core i5 processor, 3 MB cache and 16 GB memory) is used for processing of RSSI and UWB messages to carry out fingerprinting and localization. However, when the UWB devices are not in use we can do the localization on the edisons themselves.

Six Intel Edison Arduino boards were used to act as BLE beacons in this experiment using open source Bleno [22] and Noble [23] libraries for beaconing. Additionally, 12 DWM1000 UWB sensors (i.e., Decawave) were used. We

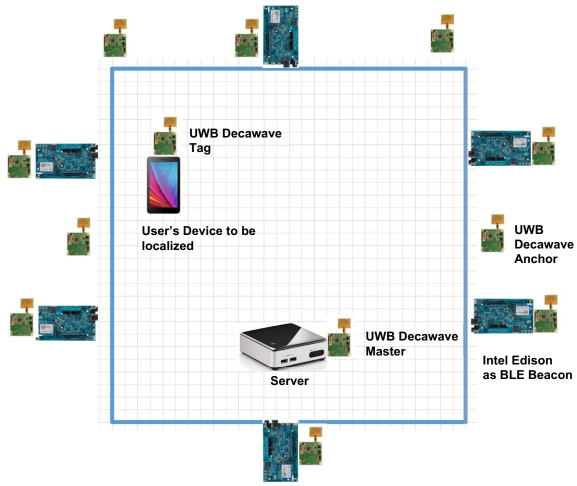

Fig. 2. Indoor localization experiment setup with 6 Intel Edison boards acting as BLE beacons; 12 UWB Decawave sensors; centralized server for sensor processing and the android tablet whose position is to be localized.

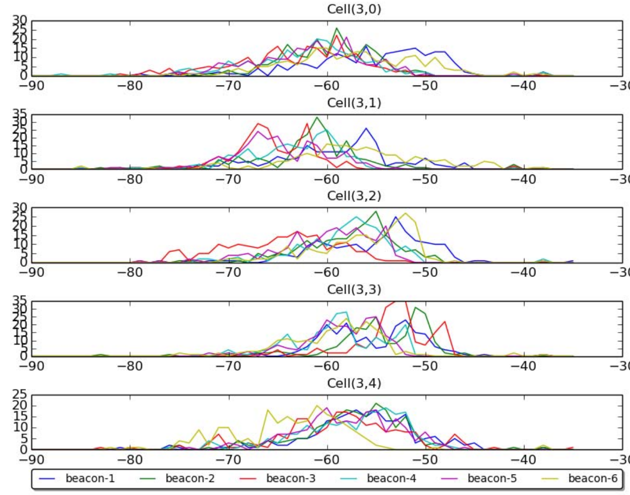

Fig. 3. Per-beacon RSSI histogram for adjacent grid cells in row 3.

expect these receivers (battery operated) to be hung at different locations in the space where the localization solution is being implemented. An Android tablet was used to simulate both the entity with the decawave sensor (high accurancy line of sight) as well as the target for BLE beacon based localization (after turning off the decawave), see Figure 2.

The Android tablet relays the RSSI messages received from all the beacons to the node doing the localization using Lightweight Communications and Marshalling (LCM) [24] publish-subscribe messaging library. LCM uses UDP Multicast for messaging and is well-suited for high-bandwidth and low-latency applications such as sensor-based localization. The localized tag's position information from the Decawave sensors is also received by the server on LCM (only when the decawave tag on the tablet was on). The server receives these RSSI messages and decawave based localized tag positions on two different LCM receiver threads. After every 300 milliseconds, a fingerprinting thread is scheduled by the server to re-compute and update the grid fingerprints. The fingerprinting thread recomputes both Expectation Maximization (EM) and Tercile-based grid fingerprints in parallel on a thread pool. The server also runs a localization thread every 30 milliseconds to perform beacon based localization of the android tablet.

During fingerprinting, the Decawave-based tag position is used as the ground truth to determine which grid-cell the tag/Android tablet is in. For a given grid-cell that the tablet is in (determined by the current Decawave-based position), 200 RSSI messages are collected per beacon (1 message is generated every 20 ms) before computing that grid-cell's fingerprint. Hence, 1,200 RSSI messages (6 beacons and 200 messages per beacon) are used for computing a grid-cell's fingerprint. Figure 3 shows how the RSSI distribution per beacon for adjoining grid-cells in row 3 differs from each other.

A grid-cell's RSSI messages for a beacon are maintained in a circular buffer, wherein new updates replace the old RSSI values in a FIFO order. When the fingerprinting thread comes up, it determines which grid-cell's RSSI values have been updated and uses the same snapshot of the updated grid-cell's RSSI values to recompute both EM and Tercile-based fingerprints in parallel.

For RSSI fingerprinting based localization, the fingerprint of target's unknown location is compared against the pre-computed fingerprints of all grid-cells to find the best match. For tercile based fingerprinting, the best match fingerprint is the one that minimizes the least squared distance from the unknown cell's fingerprint. The least squared distance for the tercile strategy is defined as sum of squares of the difference between corresponding tercile medians of unknown grid-cell u and fingerprinted grid-cell g for all six beacons. For EM based fingerprinting, the best match fingerprint is defined as the one that minimizes the least squared distance between the reconstructed Gaussian curves of unknown grid-cell u and fingerprinted grid-cell g for all six beacons. We reconstruct the Gaussian curve as represented by equation : $P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$ for RSSI values ranging from -90 to -35 using the mean and standard deviation provided by EM.

Experiment Results: We recorded the RSSI and UWB sensor data received while walking around the indoor location and this recorded sensor input was played back to perform multiple localization experiments. We changed the number of RSSI readings that are collected per beacon, also referred to as the "window" size for computing the fingerprint of the unknown grid location, so as to observe the effect of changing window sizes on the accuracy and computation time of fingerprinting. Each localization experiment was performed for different window sizes: 20, 40, 60, 80, 100 and 200 by playing back the same recorded sensor data file. Figure 4 shows the computation time of tercile and EM approaches with increasing window sizes. Though EM's computation time decreases with decreasing window sizes, EM is significantly more expensive than the tercile approach which has a compu-

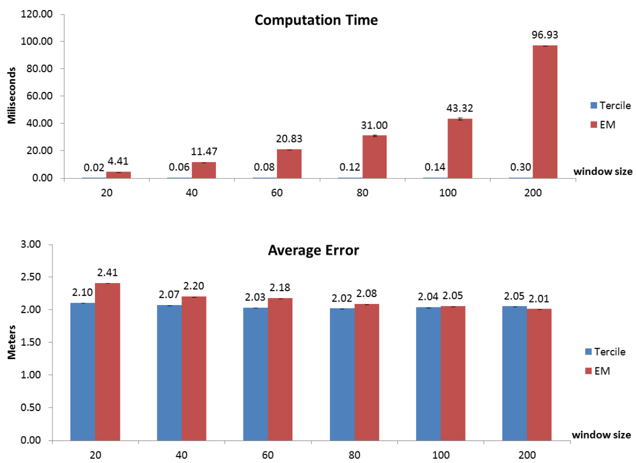

Fig. 4. Computation time and average error for EM and Tercile fingerprinting strategies with increasing window sizes.

tation time of less than 1 millisecond even for larger window sizes.

Figure 4 also shows the average error in meters for the two fingerprinting approaches. This error is the Euclidean distance between the localization result from EM or tercile strategy and the UWB based position information which is considered as the ground truth for assessing the accuracy of the two fingerprinting strategies. Since the average error for the two approaches across all window sizes is comparable (EM shows much higher error for window size=20), the tercile approach with sub millisecond computation time is preferable for fast beacon-based localization.

IV. Conclusion

In this paper, we described our composite solution for low-cost, multi-modal indoor localization based on Bluetooth Low Energy (BLE) RSSI fingerprinting and IEEE 802.15.4a compliant Ultra-wideband (UWB) RF time-of-flight based positioning. We think that this method can be extended to other indoor localization modalities such as using accelerometer and magetometer data. The user's android device forwards the received BLE signals to the central server, hence the energy consumption on user's end-device is minimal. We can further adaptively modify the frequency at which the BLE messages are forwarded to conserve energy. We additionally plan to distribute our localization and navigation algorithm over available edge devices by taking energy and resource restrictions into consideration.

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