Nuzzer algorithm based Human Tracking and Security System for Device-Free Passive System in Smart Phones Environment

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--ABSTRACT--
In recent years, majority of researches are focused on localization system for wireless environment. These researches rely on localization using devices to track the entities. In this paper, we use, a recently proposed Device-free Passive (DfP) that uses Probabilistic techniques to track locations in large-scale real environment without the need of carrying devices. The proposed system uses the Access Points (APs) and Monitoring Point (MPs) that works by monitoring and processing the changes in the received physical signals at one or more monitoring points to detect changes in the environment. The system uses continuous space estimator to return multiple location while the mortal is in motion. Our results show that the system can achieve very high probability of detection and tracking with very few false positives.

Keywords - **Device-free Passive (DfP) localization, passive radio map, nuzzer, multiple entity detection.**

I. INTRODUCTION

The human tracking system is mainly the localization process in which the person can send or receive their location using GPS .The tracking is mainly done by using the GPS, infrared, ultrasonic, and radio frequency (RF). In addition, many of these technologies require the device being tracked to actively participate in the localization process by running part of the localization algorithm. This allows the system to provide the user with its location and other services related to the estimated location. We introduce the concept in which the localization for tracking and providing security is mainly done by using the wireless communication. In the previous technique the person need to be present within the APs and MPs range for localization. If there is any disturbance due to the movement of the person then the tracking cannot take place and the whole system fails. As the whole the location was taken as the discrete space estimator so the accurate result cannot be obtained. The idea is to use installed wireless data networks to detect changes in the environment and track the location of entities passively and without requiring any devices to be attached to these entities. The DfP concept relies on the fact that RF signals are affected by changes in the environment, especially for the frequency ranges of the common wireless data networks that are currently deployed, such as Wi-Fi, or

envisioned, such as Wi-Max. By placing monitoring stations that continuously record physical quantities, such as signal strength or time-of-flight, DfP can analyze these signals to detect the changes in the environment and correlate them with entities and their locations. DfP can be useful in many practical applications including: intrusion detection and tracking for home and office applications, which could enhance the safety of law-enforcement personnel, and low-cost long-range asset protection, e.g. border protection or protecting railroad tracks, thereby increasing the value of data networks[1][2]. The DfP system consists of Access point (Aps) and monitoring point (MPs). The access point is mainly the global position system (GPS) and the mobile point is the person themselves. The GPS will get the location of the person and map it on Google map.

II. RELATED WORK

Many systems over the years have tackled the localization including the GPS system, infrared, ultrasonic, and radio frequency (RF).All these systems either require the tracked entity to be associated with a device that is being track or requires the device to actively participate in the localization algorithm. Similar to the DfP concept, radar-based techniques, computer vision based systems. However, these systems require specialized hardware and have a limited range and high installment cost, which limits their practical aspects. DfP does not require

specialized hardware. In addition it can be considered as an abstraction for such systems. DfP can be used to enhance traditional security systems, such as motion detection and video surveillance by providing non-line-of-sight detection and lower deployment cost [2]. Although the concept of DfP looks promising for a number of applications, there are a number of challenges that need to be addressed, these challenges include: handling the noisy physical signal samples to obtain consistent events recognition and tracking, tracking an entity location, and identifying an entity. In summary, the DfP localization concept is unique in detecting, tracking, and identifying entities without requiring any attached devices or active participation in the localization algorithms[1]. In addition, it works with the hardware already installed for the communication network and thus increases the value of the network used for localization.

III. TEST BEDS

In this section, we provide actual experimental results to demonstrate feasibility of the DfP concepts along with algorithms for solving the detection and tracking sub functions of the DfP problem. We defer the discussion of the identification function to the next section. We start by listing our assumptions and describing the test bed environment we used to evaluate the proposed algorithms. To evaluate the proposed techniques, we conducted two experiments. In general, a zone can be specified using different techniques. For example, each room/logical area can be assigned to a zone .Similarly, zones can be assigned based on the streams passing through them (Test bed 1).The first experiment was in a curved corridor with an area of about 24 square meters .The area is divided into five zones according to the locations of three APs and four MPs. The second experiment was performed in a larger area in the second floor of an office building, where the area (130 square meters) is divided into six zones. . The RSS for each stream i is recorded during an offline phase to calculate its variance, when no person exists in the area. 10

The access points (APs) represent the transmitting units while the wireless sniffers represent the Monitoring Points (MPs).

IV. DETECTION

Detection refers to identifying the number of entities that caused this change. In order to reduce this ambiguity, and hence enhance the reliability of detection, we combine different raw data streams to give the overall system detection. We describe two different statistical techniques to detect events. The first technique is based on moving averages and the second is based on the variance.

4.1 MOVING AVERAGE BASED DETECTION

In this technique, events are detected by comparing two moving averages of the RSSI of a single stream, with possibly different window sizes. The idea is to compare the long term signal behavior, which represents the static environment, to the short term behavior, which represents the current state, and if there is a significant change, based on a threshold, an event is detected. More formally, let q_i be a series of raw measurements over time for one raw data stream3, i.e. a *single* MP listening to a *single* access point. The averages $\alpha_{l,k}$ and $\alpha_{s,k}$ are defined as follows for time index k:

$$a_{1,k} = 1/wl \sum_{i=kb}^{k+wl-1} q_i$$

where wl and ws correspond to the window length for the two averages $\alpha_{l,k}$ and $\alpha_{s,k}$ respectively. When the relative difference between the two averages, $|\alpha_{l,k} - \alpha_{s,k}\alpha_{l,k}|$, exceeds a threshold ($\tau$), we declare an event detection for the time corresponding to $t = k + ws$. The AS computes $\alpha_{l,k}$ and $\alpha_{s,k}$ periodically to check for event detection. As noted before, the system combines a tunable number of these alerts (N) from individual streams that give simultaneous or near simultaneous detections to increase the overall system performance. The idea is to declare an event detection if N individual alerts occur within a certain period. We call this period the alert time buffer (b). Figure 4 shows the effect of the different parameters on performance. We can see from the figures that, as expected, increasing either the number of concurrent alerts used for detection (N) or the detection threshold (τ) reduces the probability of detection and decreases the number of false positives. The number of false positives is insensitive to the time buffer duration (b) and the probability of detection increases as the time buffer duration increases. The best values for the parameters are :(wl= 20, ws= 5,N= 2, τ = 0.03, b = 1). This gives a 1.0probability of detection with zero false positives.

4.2 MOVING VARIANCE BASED DETECTION

The second detection technique is similar to the first one except that it examines the moving variance of the raw data and compares it to the variance during the silence/static period. The detection criterion for any series q_i is based on the variance of the training silence/static period. For a training period [t_{start}, t_{end}], we compute the average of the variances v_t and the standard deviation of

the variance σv for the w-sized windows within it. The moving variance detection technique of the AS detect san event at time $t + w$ for a single raw stream when $vt > vt + r.\sigma v$ for an appropriate value of the parameter r. For a normally distributed variance measurements vt, values above the threshold will be r standard deviations above the mean. Again, the system combines a tunable number of these alerts (N) from individual streams that give simultaneous or near simultaneous detections, based on a time buffer (b)to increase the overall system performance. Figure 5 shows the moving variance applied to the (MP1,AP2) stream of the raw data in Figure 2. The figure shows that the system can detect the events, though one stream may not be adequate as it may lead to false positives. Figure 6 shows the effect of different parameters on the performance of the moving variance technique. The results match the intuition: Increasing the variance calculation window (w) increases both the probability of detection and the number of false positives. Increasing either the number of concurrent alerts used for detection (N) or the number of standard deviations (r) reduces the probability of detection and decreases the number of false positives. The probability of detection is insensitive to the time buffer duration (b) and the number of false positives increases as the time buffer duration increases. The best values for the parameters are :($w = 40, N = 3, r = 4, b = 0$). This gives 1.0 probability of detection with zero false positives.

V. TRACKING

In order to perform tracking, we need to capture the relation between signal strength and distance. Since the relation between signal strength and distance is very complex in indoor environments, due to the multi-path effect and other phenomena, we need to capture this relation at different locations in the area of interest through a radio map. A radio map is a structure that stores information about the signal strength at different locations in the area of interest .This is usually constructed once during an offline phase. This radio map can be constructed automatically, based on signal propagation models or can be constructed manually. We focus in this section on the manually constructed radio map and defer our discussion about the automatic construction to the next section.

5.1 PASSIVE RADIO MAP CONSTRUCTION

For the purpose of a DfP system, we call the radio map a "*passive*" radio map, in contrast to the "active" radio map constructed by the current WLAN location determination systems. Note that the radio map construction process for a passive radio map is different from the radio construction process for the traditional active radio map. For an active radio map. For constructing a passive radio map, a person stands without carrying any device and the signal strength characteristics are recorded at the MPs as received from the APs. The same difference applies to the automatic construction technique as discussed in the next section. There are different ways of constructing the radio map. We use the same method in the Horus active location determination system where we store at each radio map point the signal strength histograms from different APs. For the passive radio map building, we store at each point of the radio map the signal strength histogram for each raw data stream, where each data stream corresponds to an (AP, MP) pair.

5.2 PASSIVE TRACKING

Based on the constructed Radio map, we use a Bayesian inversion based inference algorithm to compare the received signal strength vector, which contains an entry for each raw data stream, to the signal strength at the different radio map points whose signal strength is stored in the radio map.

More formally, given a signal strength vector (s) for the signal strength readings at different MPs from different APs, with an entry for each pair of (AP, MP), we want to find the location l in the radio map that maximizes the probability $P(l/s)$. This can be written as:

$$\arg\max{}_l P(l/s) = \arg\max{}_l P(s/l).P(l)P(s)$$
$$= \arg\max{}_l P(s/l).P(l)$$

Assuming that all locations are equally probable, the term $P(l)$ can be factored out from the maximization process. This leads to $\arg\max{}_l P(l/s) = \arg\max{}_l P(s/l)$

Where $P(s/l)$ can be obtained from the constructed radio map. The two columns represent the case when we used the first experiment as a training data and the second for testing and vice versa. The results show that we can obtain tracking accuracy between 86.3% and 89.7% with simple algorithms. With an entry for each pair of (AP, MP), we want to find the location l in the radio map that maximizes the probability $P(l/s)$. This can be written as:

$$\arg\max{}_l P(l/s) = \arg\max{}_l P(s/l).P(l)/P(s)$$
$$= \arg\max{}_l P(s/l).P(l)$$

Assuming that all locations are equally probable, the term $P(l)$ can be factored out from the maximization process. This leads to $\arg\max{}_l P(l/s) = \arg\max{}_l P(s/l)$ where $P(s/l)$ can be obtained from the constructed radio map.

VI. CONTINOUS SPACEESTIMATOR

The continuous space estimator is mainly used to return the continuous location of the person. In the case of the discrete space location it returns only the single location of the person. To get the high accuracy the nuzzer is used in this. The probability of accurate location is mainly found by using two techniques. One is spatial averaging and other is time averaging.

6.1 SPATIAL AVERAGING

This technique is based on treating each location in the radio map as an object in the physical space whose weight is equal to the probability assigned by the discrete space estimator, normalized so that the sum of probabilities equals one. We then obtain the center of mass of the k objects with the largest mass, where k is a system

parameter1 <=k <= ||X||. The discrete space estimator 6 will return the location r2, assuming it is the closest in the signal strength space to the actual person location. Using the spatial averaging technique, a better location estimate can be obtained by calculating the center of mass of the top four locations (k ¼ 4).Note that the estimated location x need not be one of the
radio map locations.

6.2 TIME AVERAGING

This technique uses a time averaging window to smooth the resulting location estimates. The technique obtains the location estimate by averaging the last w location estimates obtained by either the discrete space estimator or the spatial averaging estimator. More formally, given a stream of location estimatesx1; x2; . . . ; xt, the technique estimates the current location xt at time t as: tn

$$X_t = \sum_{i=t}^{t-min(w,t)+1} (x_i)$$

VII.   HANDLING MULTIPLE ENTITIES

The previous section proved the feasibility of tracking a single entity in the area of interest. In this section, we address the problem of multiple entities identification and coarse-grained localization (zone localization). Identification refers to determining the number of entities while coarse-grained localization refers to determining the zones in the area of interest, where the multiple entities are located. Once this identification and initial localization are performed, the techniques can be applied to each zone to determine a more accurate location for the multiple entities. We describe statistical techniques, based on the variance of the received signal strength of different streams, for the identification and coarse-grained localization of multiple entities. Once the number of entities, N, is estimated, we need to determine a rough estimate of where the multiple entities are located. We recursively apply the relative variance approach to the streams passing within each zone, where for this purpose a stream represents the line connecting the AP and MP, to determine whether an entity is located inside this zone or not. More formally, given a zone covered by Nz streams, the average relative variance per zone, RVZoneav , is calculated as:

$$Rv\,zone_{aw} \;=\; \frac{1}{N_Z}\sum_{i=1}^{Ni}\sigma on\,i^2$$

The N zones with the highest relative variance are returned as the estimated zones.

7.1 Identifying the Number of Entities

Our approach is based on using the relative variance, i.e., the ratio between the variance of the human presence to silence periods as a feature for identifying the number of entities. The idea is that as the number of entities in a given area of interest increases, the average relative variance of all streams covering this area also increases. More formally, let Ns be the number of streams covering the entire area. The value of RVav is then compared against different thresholds to determine the number of entities. The system declares that there are N entities in the area of interest if N <RVav< Nþ1, where _N and _Nþ1 are the Nth and the N þ 1st thresholds.

7.2   Multiple Entities Zone Localization

Once the number of entities, N, is estimated, we need to determine a rough estimate of where the multiple entities are located. We recursively apply the relative variance approach to the streams passing within each zone, where for this purpose a stream represents the line connecting the AP and MP, to determine whether an entity is located inside this zone or not. More formally, given a zone covered by Nz streams, the average relative variance per zone, RVZoneav .The N zones with the highest relative variance are returned as the estimated zones. As a final note, we point out that localizing entities to within zones also enhances the scalability of the technique. On the one side, zones reduce the computational requirements of the system as it limits the number of radio map CDFs of zone difference error for localizing multiple entities. A zone difference of zero means an exact match. Locations to be processed. On the another side, because each zone is processed using the streams that mainly have an effect in it only, this makes the zones virtually independent from each others. This becomes even more valid as the scale of the environment increases, as the set of APs and MPs covering the area would change. Consequently, the number of sampling points becomes independent from the number of people as we can calibrate using one person only. In summary, the scalability is enhanced when the system uses the multientity detection technique as follows:
1) Identify the number of persons in the environment;
2) Identify the active zones;
3) For each identified active zone person tracking using the streams that are mainly affected in the identified active zone.

VIII.   DYNAMIC CHANGES IN ENVIRONMENT

Changes in the environment due to the time of day and day of year, such as temperature and humidity, can make the operational environment different from the environment used in constructing the radio map, and hence may reduce accuracy. Note that for the DfP problem, changes in people activity patterns should have little effect on the system, as the system typical environment is at periods where no one is expected to be in the area of interest. For environmental changes, based on the experience from the device-based active localization systems, their effect is limited. Another possibility is to use multiple radio maps, corresponding to different

environmental conditions. An automatic passive radio map construction tool can aid in solving this problem by capturing the effect of these different changes. Our experiments, presented, use an independent test set separate from the one collected during the offline phase. This quantifies the effect of the dynamic changes in the environment.

IX. CONCLUSION

We presented the design, implementation, and evaluation of the Nuzzer DfP localization system. We evaluated the performance of the Nuzzer algorithm. Our results have established the proof of feasibility of the DfP concept. In order to get it to the point that it can be commercially deployed we have to tackle a number of challenges. We identified different challenges for realizing the DfP system and give directions on how to address them. In particular, we believe that the problem of automatic construction of a passive radio map is an important challenge that needs to be addressed for more understanding of the other DfP challenges and possible solutions. We also believe that research in the DfP challenges identified in this paper, not only will have a major impact on the DfP systems, but also is of value to other localization technologies. Currently, we are expanding the system in different directions including: Automatic generation of the passive radio map, optimizing the APs and MPs positions, and analyzing the effect of dynamic changes in the environment and different hardware.

REFERENCES

[1]   Moustafa Seifeldin, Ahmed Saeed, Nuzzer: A Large-Scale Device-Free Passive Localization System for Wireless Environments, *IEEE Transaction on Mobile Computing, VOL.* 12, NO. 7, JULY 2013.

[2]   Wagner.B, Device-free user localization utilizing artificial neural networks and passive RFID, *Ubiquitous Positioning, Indoor Navigation, and Location Based Service (UPINLBS)*, 2012.

[3]   Matthew Mah, Challenges: Device-free Passive Localization for Wireless Environments, Infocom, Proceedings *IEEE*, 2012.

[4]   M.Ponnavaikko, Location Update Accuracy in Human Tracking system using Zigbee modules, *(IJCSIS) International Journal of Computer Science and Information Security*, Vol. 6, No. 2, 2009.

[5]   M. Youssef and A. Agrawal, The Horus location determination system, *ACM Wireless Networks (WINET) Journal*, 2007.

[6]   M. Youssef, M. Mah, and A. Agrawala, Device-free passive localization, *Technical Report CSH860,*

UMIACS-TR-2007-13 Department of Computer Science, University of Maryland, 2007.

[7]   M. Youssef, M. Mah, and A. Agrawala, Device-free passive localization, *Technical Report CSH860, UMIACS-TR,* 2007-13

[8]   M. Youssef, A. Youssef, C. Rieger, U. Shankar, and A.Agrawala, Pinpoint: An asynchronous time-based location determination system, *Proceedings IEEE*, June 2006.

[9]   Hyuk Lim, Lu-Chuan Kung, Jennifer, Zero-Configuration, Robust Indoor Localization: Theory and Experimentation, *Proceedings of ACM Multimedia*, 2003.