CAPTURE - Cooperatively Applied Positioning Techniques Utilizing Range Extensions

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CAPTURE - Cooperatively Applied Positioning Techniques Utilizing Range Extensions

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***Abstract*— The most commonly implemented Indoor Location Based Solution uses existing Wi-Fi network components to locate devices within its range. While this technique offers obvious economic rewards by utilizing a preinstalled infrastructure, these network topologies were typically designed to provide network coverage to mobile devices rather than deliver an Indoor Location Based Solution. Large areas without coverage are common in these networks because network designers were not typically concerned about providing 100% coverage for mobile data. Hallways, toilet areas or other general purpose areas that ordinarily would not require network coverage did not get dedicated WAPs installed. Transient users navigating these areas of the network were un-locatable using this infrastructure. Furthermore the indoor arena is an especially noisy atmosphere, being home to other wireless devices such as Bluetooth Headsets, Cordless Phones and Microwave Ovens. Considering users spend more time in an indoor environment, over 88%, the need for a solution is obvious. Therefore, we propose a solution to resolve the issue of restricted coverage of Indoor Location Based solutions, using a cooperative localization technique - Cooperatively Applied Positioning Techniques Utilizing Range Extension (CAPTURE). CAPTURE offers a method of locating devices that are beyond the range of the current in-house location based solution. It presents a unique contribution to research in this field by offering the ability to utilize devices that know their location within a Location Based Solution (LBS), to evaluate the position of unknown devices beyond the range capacity of the LBS. This effectively extends the locating distances of an Indoor LBS by utilizing the existing mobile infrastructure without the need for any additional hardware. The proliferation of smart phones and the tablet form factor, bundled with Wi-Fi, Bluetooth and gyroscopes – technologies currently used to track position, provide a fertile community for CAPTURE to cooperatively deliver a location solution.**

Keywords — Localisation; Indoor positioning; Indoor localisation; geographical positioning; wireless.

I. Introduction

On loosing something or forgetting where you last placed something, a common piece of advice is to retrace your steps back in your mind. This can be quite a formidable task given the multimodal transport available today coupled with the complexity and scale of buildings we interact with on a regular basis. The ability to place an avatar of yourself onto a map to graphically retrace your steps in real-time would dramatically reduce the brain power required to remember everywhere you were at a given time. Googles manoeuvring into the indoor location mappings realm [1] opens up the opportunity to deliver this virtual reality, currently being able to provide door to door route planning. Being able to navigate your way from your office desk out through your company's building (taking the stairwell to avoid your boss in the lift) is eminently achievable albeit with a small number of locations on a modern smartphone using google maps. A level switcher allows you to onion slice through multiple floor level plans, before switching to GPS to offer possible transport alternatives through the outdoor environment. On reaching what '*historically*' would have been your destination, Google Indoor Maps and more importantly an Indoor Positioning System (IPS) picks up where GPS left off offering a point to point navigation solution. This can then take you through the complexities of an airport terminal for example, via specific waypoints such as security and check-in desks directly to your departure gate.

One of the barriers to implementation of such a concept is the limitation in coverage and accuracy of currently implemented Indoor Position or Location Based Systems [2]. IPSs typically utilize pre-existing Wi-Fi network infrastructure taking ranging information from Wireless Access Points (WAP's) as inputs for a localization algorithm. Unfortunately the drivers behind the strategic decisions on the positioning of WAPs, in a Wi-Fi based solution, were typically to catch large congregations of users and primarily to provide the highest available throughput to those users. Coverage for IPSs is not necessarily to the forefront of network designer's minds when designing such networks, leaving large areas beyond the range of an IPS. GPS on the other hand, offers near global coverage, bar some issues with urban canyons and other high rise natural obstacles that prevent Line of Sight (LoS) to the just under 30 satellites required [3] to deliver such wide scope.

The indoor environment does not afford such clear unobstructed views to and from tracking devices, the many doors, walls, floors, pillars and ceilings hinder the capacity of an IPS to locate devices. Furthermore the indoor arena is an especially noisy atmosphere, being home to other wireless devices such as Bluetooth Headsets, Cordless Phones and Microwave Ovens. All of these devices operate in the same frequency band as the Wi-Fi solution, namely 2.4 GHz and therefore can interfere with the reception of signals used to locate [2], making them behave in an unpredictable fashion.

These environmental dynamics combine to dramatically affect the ability of an indoor solution to provide an acceptable level of coverage. Literature from Yang [4] and Rowe [5] reflect that Location Awareness is rapidly becoming a fundamental requirement for mobile application development. This highlights the challenges posed for ubiquitous localization of devices in the indoor arena. Considering users spend more time in an indoor environment, over 88.9% according to a recent Canadian study [6] , the need for a solution is obvious. We propose a solution to this issue of coverage limitations by using a cooperative localization technique, CAPTURE. CAPTURE can plug into an in situ solution irrespective of the technology or location technique that solution currently uses to locate. It provides a location relative to the devices locating it, which can then be mapped onto a global overview of the Location Based System (LBS), assisting in the aforementioned scenario to get you to the departure gate in a point to point navigation solution.

Consider the following scenario where a user ‘Bob’, is in his favorite seat in the library, unfortunately the seat is in the far corner of the library, which can only be ‘seen’ by one Wireless Access Point. In this position Bob’s tablet can gain Wi-Fi access through this Access Point to allow him access to online resources. However one Access Point is not enough for the in-house Location Based System to accurately locate Bob within the building using Trilateration positioning techniques. Sue is sitting near the front of the library and can be ‘seen’ by 4 Wireless Access Points, and is thereby accurately located on the Location Based System. She is also 25 meters to the left of Bob and the Wireless Network Card on her Laptop can see Bob’s tablet. The Librarian is stacking books on the shelves behind where Bob is sitting and her smartphone is currently located within the Location Based System also. The wireless NIC on her smartphone can also ‘*see’* Bob’s tablet, therefore, in a normal scenario, Bob would be beyond the range of the Location Based System, but because CAPTURE can use the known positions of the Librarian and Sue and Bob’s position relative to them it can accurately estimate Bob’s position within the library.

The rest of this paper is laid out as follows; Section II describes the system model used to implement CAPTURE. Section III provides an overview of the experimental test bed used to evaluate the solution and Section IV documents the data collected during test. In Section V we describe the findings of the experiments that were carried out validating the feasibility of the system, the penultimate section, Section VI outlines the proposed implementation of CAPTURE and the paper closes with a conclusion in Section VII, providing an insight into some projected future work with CAPTURE.

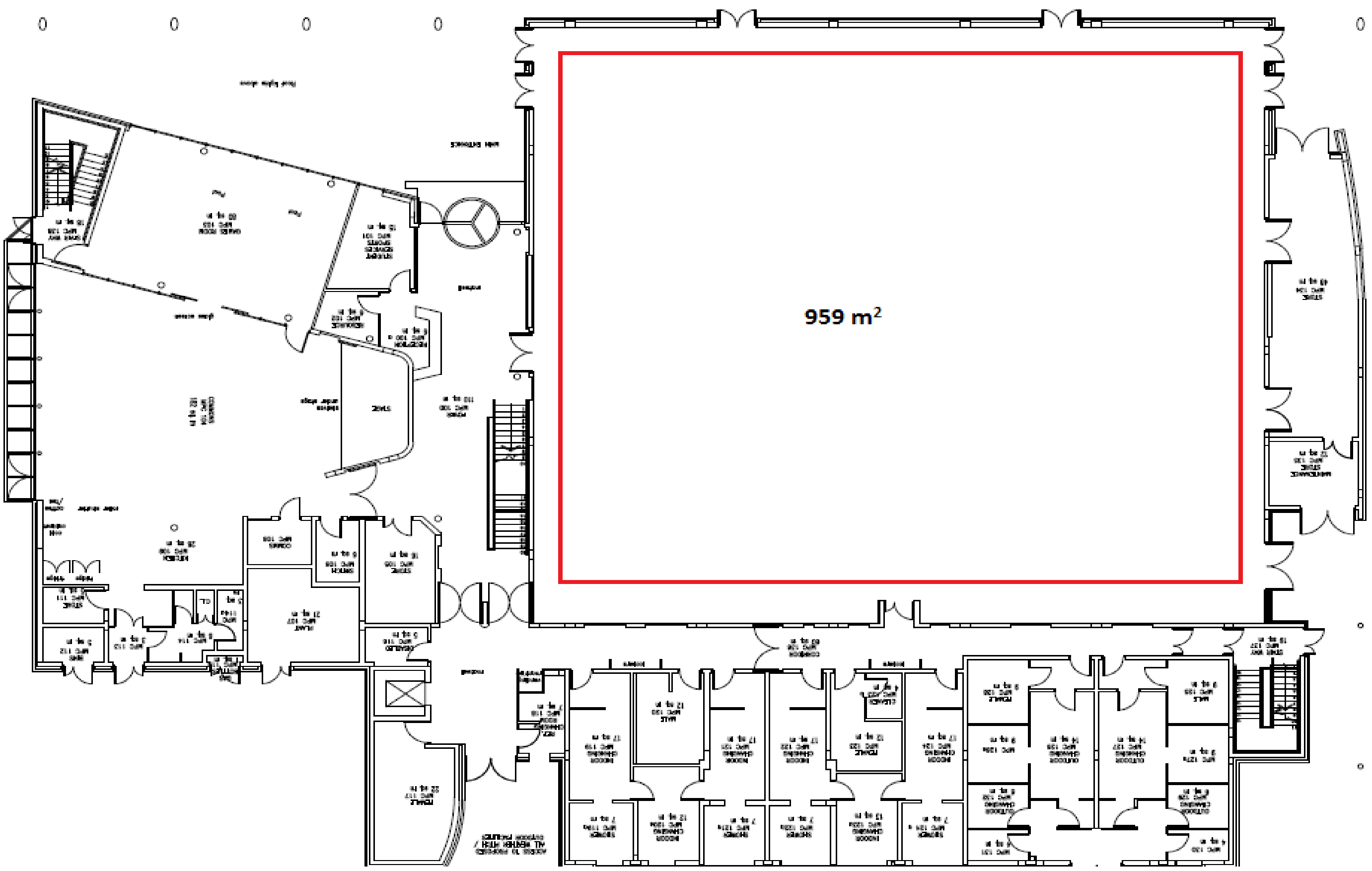

Figure 1: An Danlann Sports Hall LyIT

II. CAPTURE - System Model

This section describes a system model that can be used in a localization solution to establish the Cartesian coordinate values of a lost device within a two dimensional plane. CAPTURE does not require a preceding calibration stage or a site survey, providing a robust opportunistic solution in dynamic environments, using only real time RSSI values without changing the IEEE 802.11 network. Literature within the realm of Location Based Systems frequently use terms such as Anchor or Anchor Nodes to describe devices that help to determine the position of lost or unknown devices. The term anchor elicits a perception of a static or permanent device, which in a cooperative solution these devices most certainly are not. For this reason we will use the term reference device when describing devices that assist in the positioning of lost or unknown devices.

Two key components typically make up the estimation of the position of a lost device. First of all ranging techniques are used to estimate the distance from the transmitting device(s) to the receiving device(s). This is calculated using a metric for example the length of time it takes a signal to propagate the distance from the transmitter to the receiver. The second component is the position estimation technique, here the ranging variables are calculated using one or more ranging techniques and these are used as input for an estimation algorithm (mathematical formulae) to calculate the position of the lost device.

A. RSSI – Received Signal Strength Indicator

Possibly the most popular ranging technique used in Indoor Localization, Received Signal Strength Indicator (RSSI) is a measurement of the voltage that exists in a transmitted radio signal, which is an indication of the power being received by the antenna. When a signal first leaves a transmitting device, the power of the signal drops or attenuates, this is true of both wired and wireless transmissions. As a radio signal propagates through the air some of its power is absorbed and the signal loses a specific amount of its strength, therefore, the higher the RSSI value (or least negative in some devices), the stronger the signal. Knowing the amount of signal loss over a given distance provides a method to calculate the distance from a transmitting device, given a Received Signal Strength. At its most basic level this allows for the 'coarse' localization or as referred to in other literature, 'presence-based localization' [7] of a device relative to the transmitting device. This can be illustrated by the RSSI calculated distance being the radius of a circle and the 'searching' device being at the center of that circle. The estimated position of the lost device is anywhere on the circumference of that circle. In an IEEE 802.11 network if the locations of the Access Points are already known, then the location of Mobile Devices traversing the network can be located relative to them, albeit only to the circumference of the radius of the calculated distance. Further localization algorithms and position estimation filtering techniques must be applied to provide a more precise level of localization.

In a cooperative paradigm, mobile devices can simulate the role carried out by Access Points providing a relative reference to a lost devices location. RSSI values can be extracted from beacons transmitted between devices within range. Correlation of these signal indicators and distance can be estimated using many of the methods already applied throughout literature in this arena [8-11]. RSSI based or more broadly speaking, Wi-Fi based Indoor Positioning Systems have had notoriously irregular environment variables such as reflection, refraction, diffraction and absorption of radio waves that can impact positioning estimated dramatically [12]. Although RSSI is a measure of signal loss, it is not a linear representation of how many dBm is actually reaching the card. If a signal indicator is reading -72, this means that it is 72 dBm less powerful by the time it gets to your device. Experimental test carried out at an early stage with CAPTURE further extoled this assumption. Results of these tests can be viewed in Table 1: 5 meter increments in Section V, Data Collection and Presentation. Crudely extracting the RSSI at given distance increments to attempt to derive a meter distance being equal to a given dBm increase in RSSI reading was not going to yield any value worth using in any further experiments. The authors in [13] advocate a solution utilizing a RSSI smoothing algorithm to minimize the dynamic fluctuation of the RSSI values.

B. Trilateration

Trilateration is a key component of GPS position estimation techniques. It is a process that can estimate the position of a mobile device given the positions of at least three other objects and the distance from those objects to the device to be located. In the scenario depicted below in Figure 2(a), illustrated using a cooperative localization example, the circle depicts the distance from a reference device to a lost device. This distance would have been derived using the RSSI value between the reference and lost devices. All we can say about the whereabouts of the lost device is that it resides somewhere on the circumference of the circle that is constructed using the radius of the estimated measurement between the two devices. A second reference device will allow the position of the lost device to be narrowed further as can be seen in Figure 2(b). Now the ranging estimates of the lost device have been calculated relative to the second reference device also. Therefore considering the lost device must be on the circumference of the circles created by the distance between it and the two reference devices there are only 2 possible positions where it might be, the intersections of these two circles.

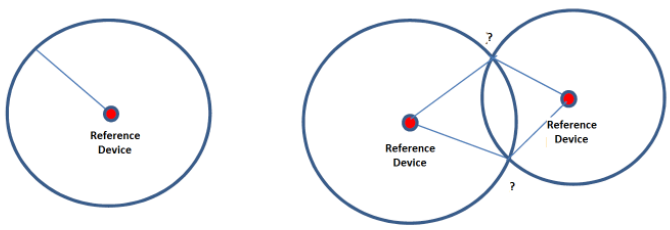

Figure 2 (a) Single Distance (b) With 2nd Reference Device

To calculate the exact position of the lost device we need a third reference device. When we calculate the distance from this final reference device to the lost device and considering we already know the distance from the other reference devices. We can then determine that the lost device can only be at one specific position to match those three particular distance estimations – the intersections of the three circles (see Figure 3). The ranging estimates calculated from the RSSI values in the tests were used as the inputs for the trilateration algorithm on the CAPTURE, to provide an estimate on the position of the lost phones.

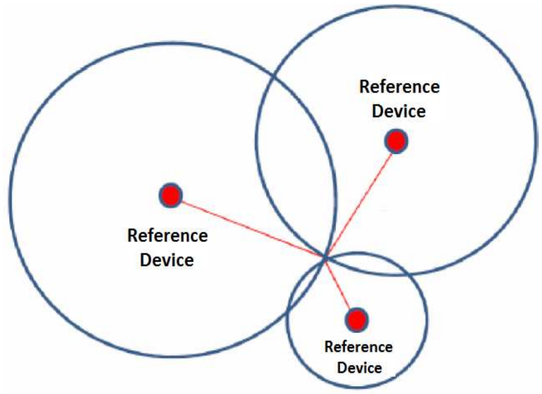

Figure 3: Trilateration Example

II. Experimental Test Bed

In this section, we will provide evidence showing the suitability of CAPTURE as a solution to the indoor ranging problem. To do that we carried out a large campaign of measurements in the An Danlann Sports Hall in Letterkenny Institute of Technology illustrated in figure 1. The hall offers a 40m diagonal testing range, providing Line of Sight measurements for all tests, as can be seen in the picture depicted in figure 4. When readings were been recorded all users vacated the hall, this provided an optimal environment to use as a benchmark for future tests on CAPTURE.

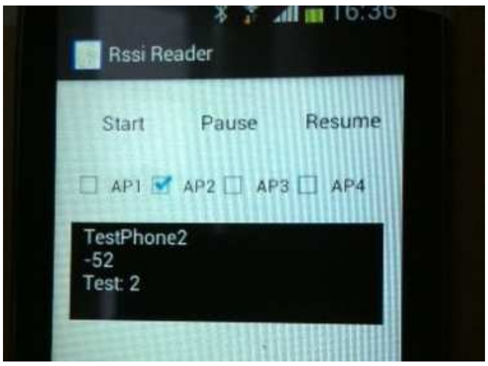

Figure 4: Test Environment

Each phone used in the test is given a name (BSSID) TestPhone1, TestPhone2 for example. CAPTURE reads the RSSI of all available reference points, i.e. all devices it can 'see', but it filters out only the test phones selected by the user carrying out the tests. This can be seen in the image in figure 5, and is achieved via a lookup table mapping the MAC address of the phone to the phone name. This allows the use of only a specified phone or a group of phones during any given test.

Figure 5: CAPTURE Client Interface

A. System Components

The experimental setup of the prototype consisted of the following system components:

- Mobile Devices

5 Samsung GT-S5310 Galaxy Pocket phones, running Google Android 2.2.1 on a 600 MHz ARMv6, Adreno 200 GPU, Qualcomm MSM7227 chipset, were used to carry out the evaluation of the CAPTURE system. 4 of the phones were used as reference devices, the other phone acted as the lost device. All phones used during the test were of an exact make and model so as to rule out any issues with varied RSSI reads with different antenna types, some of these issues have been described in the literature [14, 15]. Lisheng et al., [15] go so far as to discribe the distortion being as much as 11.2 dBm out with different antenna types over a 25 meter read range. During the tests all phones were place at a distance of 80cm above floor level, to mimic as close to a real world example of a user holding them. The phones were placed on identical platforms during the tests to negate the impact of Hand-Grip body-loss effect which can also impact ranging measurements as documented in litrature by Rosa et al., [16]. Kaemarungsi and Krishnamurthy highlighted in their litrature [17] that device orientation can also introduce errors when calculating signal range estimates, so all phones had the same orientation when used in our tests.

- Database

A MySQL Server version: 5.0.96 hosted on a Linux platform was used to store all data collected by the devices. The server was online and the phones wrote directly to it as they recorded RSSI values from each other. The data was then passed through a low level filter to remove any outliers, before an average RSSI reading was calculated for each required ranging measurement, to be used in the trilateration algorithm to estimate the position of the lost device.

- Laptop

A Dell Latitude E6440 iCore3 running Windows 7 Professional was used to develop the app to gather the RSSI from the phones. An algorithm was designed to convert this RSSI reading into a ranging measurement before a trilateration algorithm converted the ranging measurements into Cartesian coordinate values. We used the Eclipse IDE and Android Software Development Kit (SDK) for Android development and debugging, to develop the app.

B. Ranging Measurement Estimation

The RSSI values captured from the beacons transmitted by devices within range of the 'lost device' were used to estimate the relative distance between them. As explained earlier RSSI values do not provide a linear representation of distance. The authors in [13] advocate using the formula in "(1)," below to estimate RSSI, and thereby extrapolate distance given RSSI:

$$RSSI = -(10n \, Log_{10}(d) + A) \qquad \text{Equation (1)}$$

Where:

n: Path Loss Exponent

d: Distance from transmitting device

A: Received signal strength at 1 meter distance

The path loss exponent typically varies from 1.5 to 4, with 1.5 representing a free-space Line of Sight (LoS) value and 4 representing an environment that incorporates a high level of signal attenuation. Not having a good equation modeling the environment in which your experiments are to be deployed, will be reflected in horrible results. After initial pre-tests were evaluated, a Path Loss Exponent of 1.5 was determined for the test environment, because of the open plan design of the Hall offering LoS between all devices and the RSSI at 1 meter was measured at -43.6316. The results of the collected data are illustrated in the following section.

III. Data Collection and Presentation

Here we present all of the data collated throughout this work, the data sets are illustrated in the graphs and tables. During the recording of data the hall was emptied of people so as to provide a clean set of results. An initial test was run to establish the 1 meter range for input into the algorithm in equation 1, the results of this test can be seen in figure 6.

Over 500 readings were recorded at various locations throughout the hall, to accurately obtain the meter value for the algorithm, these were smoothed with a filter before the average was calculated.

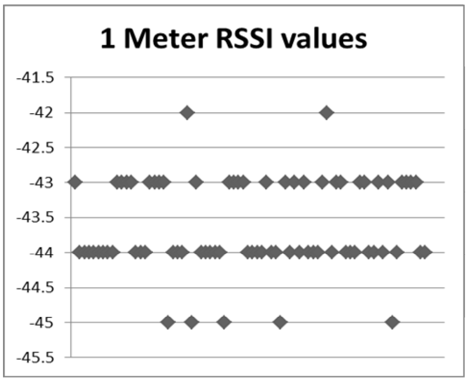

Figure 6: Meter RSSI values

Further tests were then carried out to measure the accuracy of both the RSSI values received and the resulting range estimations from the algorithm. Table 1 below, depicts the results of tests to capture the RSSI values between two phones at 5 meter increments diagonally across the hall. It highlights the RSSI value beginning at -52.48 for the 0-5 meter range. A sample set of 200 readings was recorded per section, an average was then taken from this set. The standard deviation was also documented to illustrate any fluctuations in the received values, typically these were found to be low during our tests.

Distance	0 - 5 m	0 - 10 m	0 - 15 m	0 - 20 m
Average	-57.264	-61.5652	-69.5263	-67.5662
Std Dev	0.4996	0.4	0.85346	0.48332
Estimate	4.517	8.269	25.31	19.216
Distance	0 - 25 m	0 - 30 m	0 - 35 m	0 - 40 m
Average	-68.38	-70.75	-71.854	-73.681
Std Dev	0.6884	0.9797	0.6803	0.7901
Estimate	21.544	30.059	35.104	45.379

Table 1: 5 meter increments

The average was then inputted into the algorithm to derive a range estimate based on the RSSI values received. As mentioned before RSSI values do not provide a linear representation of measurement, and therefore some of the increments do not initially seem like they could assist in finding a distance at a given measurement. The trilateration algorithm accounts for an error bounds of 2.5 meters in the range estimation of the RSSI value. One notable issue with the recorded RSSI values was the reading taken at the 0-1 meter distance however. It jumped dramatically at this distance, giving a RSSI value higher than the 0-20 and 0-25 meter tests. This test (0-10 meters) was carried out at different areas of the hall, to try and rule out signal interference. But irrespective of which location the reading were taken the RSSI value was always higher (or more negative) than the next 3 larger tests. No reason could be given at the time of writing for this anomaly within the set.

IV. Experimental Results

Figure 7 depicts one of the tests were CAPTURE accurately locates a lost phone within 2.5 meters. TestPhone1, TestPhone2 and TesPhone3 know their location, via the in-house IPS. They also know the distance between themselves (TestPhone1 - TestPhone2 = 15 meters, TestPhone1 – TestPhone3 = 13 meters and TestPhone2 – TestPhone3 = 17 meters), the RSSI readings from the Lost Phone to TestPhone1 is -61.5551dBm, from the Lost Phone to TestPhone2 is -65.34534 dBm and from the Lost Phone to TestPhone3 is -61.8952dBm. These RSSI readings translate to a ranging estimate of 13.345, 15.1221 and 9.349 meters respectively when put through the ranging algorithm. The actual distance between TestPhone1 and the lost phone is 11.5 meters, between TestPhone2 and the lost phone is 13.2 meters and TestPhone3 and the Lost Phone is 11.96 giving an approximate error rate of 2.5 meters.

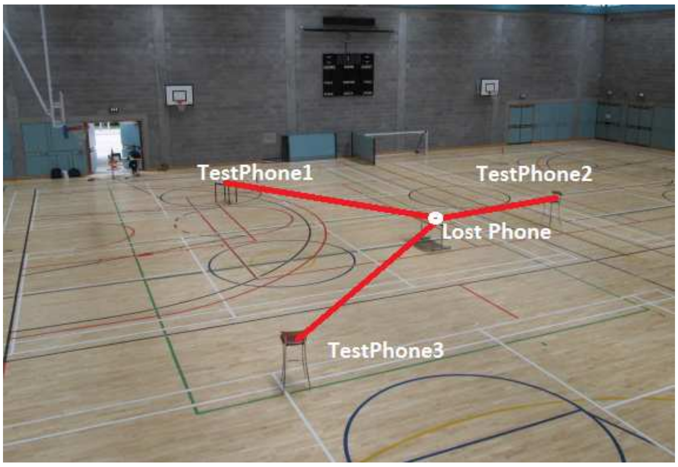

Figure 7: Finding Lost Phone

V. CAPTURE – System Implementation

In order for CAPTURE to be able to cooperatively locate a lost device within a network, there must be at least 3 reference devices within sight of the lost device. Each of these must have 'a prior' knowledge of their location within a pre-existing localization solution.

The hypothesis of CAPTURE was to extend the range of in-house IPS's, and tests shown have proven that it can achieve exactly this. Existing IPS's have dramatically more powerful infrastructure than what CAPTURE would utilize though. For example 230 volt AC powered Access Points in a standard IPS versus 12 volt DC powered mobile reference devices (smart phones, tablets and\or laptops) in a cooperative solution. It would be naive to think that accuracy levels of an in-house IPS would also 'extend' to a cooperative model, although this does not take away from the solution to the range issue that CAPTURE provides. The implementation of a more comprehensive filter would nonetheless assist with accuracy the Kalman or Extended Kalman Filters are recommended in the following literature [18, 19].

VI. Conclusion

This paper introduces CAPTURE a cooperative localization system that provides a solution to the problem of devices being out of range of a hosted Indoor Positioning System. Experiments with the CAPTURE system have demonstrated that utilizing a cooperative framework of mobile devices can extend the range of an in situ Indoor Positioning System by at least the range of the outermost devices located within the system.

Some issues arose during testing for example the 0-10 meter readings, and this necessitates further work. A more comprehensive algorithm would provide more accuracy for the system. An expansion of CAPTURE to avail of Bluetooth 4.0 would allow for the extension of an IPS incorporating some of the advantages of this technology. Bluetooth has been used as a cooperative solution to the accuracy issue in IPS's and can be seen in the following literature [20, 21]. Further investigation into the incorporation and evaluation of Wi-Fi Direct as a solution is also warranted.

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