**Section 1 - Introduction**

Location based services (LBSs) are mobile applications that rely on a user’s location to provide context aware functionality [1]. LBSs require the location of the item to provide its functionality. GPS is a very popular technology for LBSs, however is not suited for an indoor environment [1]. Some specially developed systems, like active badge, cricket and Radio Frequency Identification (RFID), are capable of indoor localization, however, require specialised equipment.

A Wireless Local Area Network (WLAN) is aimed to provide local wireless access in fixed network architectures. WLAN is extremely popular as a communication medium for trafficking general information in computer networks and is today the industry standard [1]. It is used in outdoor public areas too [2]. The IEEE 802.11 working group initially published a wireless networking protocol in 1999, named 802.11b and later, 802.11g. Most of the WLAN products are based on 802.11b and operate in the 2.4GHz radio band.

WLAN can not only be used for communication, but indirectly for positioning [1,2]. As WLAN technology is already popular in indoor environments, it is an attractive technology to use for indoor asset tracking, as no extra network infrastructure is needed.

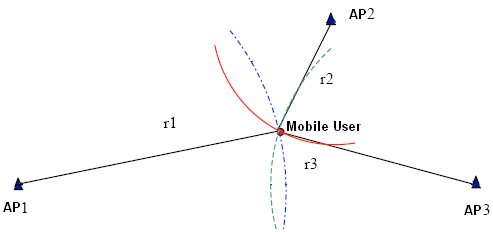
**Section 2 - Background**

Several techniques have been implemented for locating wireless nodes, that are irrespective of what technology is being used to locate them. Most techniques fall into two categories, **triangulation** and **fingerprinting**. These categories are explained in section 2.1, for the purposes of comprehension later in the paper. Section 2.2 reviews previous work done in the field of WLAN tracking techniques and is followed by a comparison of the work reviewed in section 2.3. Section 2.4 is a summery with respect to the experiments and techniques reviewed.

**Section 2.1 – Basic theory of triangulation and fingerprinting**

The triangulation approach is a relatively easy (but less effective) technique. Three or more Access Points (APs) are positioned in the environment and their coordinates are recorded. If the distance r from the AP to a mobile user can be measured, a circle with radius r can be drawn that will represent the possible position where the mobile user is located. With two other AP’s forming two more circles, the location of the mobile user can be identified as the geometrical coincident point [1]. See Figure 1.

Figure 1: Triangulating a mobile user[[1]](#footnote-2)



The triangulation technique consists of 2 steps [1]: The first step is to determine the average signal strength over a short period of time between the 3 AP’s and the mobile user. The second step is to compute the location based on the distances derived from the SSs of the 3 AP’s.

The difficulty with a plain triangular approach is that the distance is hard to accurately determine from the signal strength in an indoor environment as signal strength can be hindered by several factors [5]:

* penetration losses from travelling through walls and floors
* multipath propagation, the distortion or cancellation of a signal due to the effects of it arriving via multiple paths due to reflection off surfaces [8]
* and basic attenuation due to distance travelled

The above mentioned problems are due to specific environmental aspects. Overcoming these factors is what fingerprinting addresses. By testing the received SS at known locations, the hindering of the SS due to constant interferences can be accommodated [1]. The apparent location based on SS received at a location is now pre-mapped to the true observed location. The use of reference points (RPs) means the training phase becomes a significant task in terms of labour and time [5].

Problems that pertain to mobile user localization in general, is the interference from other devices such as microwave ovens, Bluetooth devices, cordless phones [1] and people moving inside the building [2]. The fingerprinting technique cannot directly alleviate such interferences. Probabilistic algorithms can be used to reduce such sources of inaccuracy, as done by Ladd *et al* [2], which is discussed later.

The fingerprinting technique consists of two phases: training and positioning. The objective of the training phase is to build a fingerprint database of identifiable reference points (RPs) that have been carefully preselected in the environment. At each RP the signal strengths of all the APs are measured and the characteristic feature of that point is identified [1]. In the positioning phase (the real time phase), the mobile user’s signal strengths are determined and compared to those in the database. An appropriate search/matching algorithm localizes the mobile user to the respective RP [1].

Search/matching algorithms of SS data that have been used to date can be broken down into **deterministic** and **probabilistic** methods [1].

The deterministic approach uses a relatively simple database [1]. The database houses each RP and associates *x* received signal strengths with it, where *x* is the number APs used. When localizing a mobile user, the signal strengths of the *x* readings obtained in real time is compared to the tuples in the database.

The probabilistic method requires a lot more data sampling during the training phase. During training, the SS variance with respect to time is recorded as well. This provides sufficient information to apply Bayesian theory. Bayesian inference algorithm is possibly the most powerful localization algorithm to date [2]. As it relates the conditional and marginal probabilities of two random events, it can improve accuracy of apparent signal strength. Fingerprinting has received a lot of attention [1-7] in particular with respect to probabilistic approaches to dealing with received signal strength. As proved by Youssef *et al.* [3], probabilistic methods outperform deterministic methods all round, but are more computationally expensive.

**Section 2.2 – Review of work done in WLAN device localization**

Li *et al.* [1] tested the triangulation and deterministic fingerprinting approaches on a stationary device. The simplicity of the triangulation approach was apparent. Tested within the same environment as the experiment done in the fingerprint experiment, the accuracy was between 4-5 meters. The fluctuation of the accuracy is due to signal strength variation between the remote node and the AP. In the deterministic fingerprinting experiment, several selection algorithms for which RP best represents the position of the user were tested: the Nearest Neighbour algorithm (NN) [6], k Nearest Neighbour (KNN) for k = 2 – 6 and k Weighted Nearest Neighbour (KWNN) for k = 2 – 5. A NN algorithm selects the closest RP to the apparent location [1]. A KNN algorithm localizes the mobile user to the coordinates that represent the mean of k NNs [1]. KWNN applies KNN but the resultant coordinate is the weighted mean of the k NNs [1].

In this experiment they achieved accuracy as low as 1.19 meters distance error (132 RPs, 4 KNN). Despite the relative computational simplicity of the NN techniques, they have proved to be very effective [4]. Although 1.19 meters is the highest accuracy, 132 RPs requires a lot of time to train. An accuracy of 1.72 meters was achieved by simply lowering the number of RPs to 33. This result was obtained using the 4NN algorithm. A summarized version of the results is shown in Table 1.

Table 1: Summarized version of results of Deterministic Fingerprinting localization

|  |  |  |  |
| --- | --- | --- | --- |
|  | **NN (m)** | **4NN (m)** | **4WNN (m)** |
| **Test1 (132 RPs)** | 1.75 | 1.23 | **1.19** |
| **Test2 (99 RPs)** | 1.63 | 1.31 | 1.27 |
| **Test3 (66 RPs)** | 1.74 | 1.6 | 1.49 |
| **Test4 (33 RPs)** | 1.78 | **1.72** | 1.64 |
| **Test5 (16 RPs)** | 2.55 | 2.98 | 2.45 |

There were 5 APs available in the environment.

Ladd *et al.* [2] tested the probabilistic fingerprinting approach on both moving and stationary WLAN devices.

Their experiments were done in an empty corridor that was 32.5 meters long. There were 5 APs within the device’s range, but the exact coordinates were not given. Their experiments were done with no persons allowed to be within area where their experiments occurred. 1 of the 4 approaches they tested was the use of sensor fusion. Sensor fusion is the combination of multiple independent observations to obtain a more robust and precise estimate of the measured variables [2]. Although one may think the use of multiple APs is the use of sensor fusion, it is in fact the implementation of much more technical use of the variance data of multiple APs. Their work included the following 4 experiments:

1. Static localization using the position of maximum probability as calculated by Bayes’ rule.
2. Static localization using the position of mean maximum probability as calculated by Bayes’ rule over 1 second.
3. Localizing a moving device using the position of maximum probability as calculated by Bayes’ rule.
4. Localizing a moving device using the position of maximum probability as calculated by Bayes’ rule and implementing sensor fusion.

The summarized results are presented in Table 2. As extensive testing was done, I suppressed the results to the probabilities derived for the position error being within 1.5 meters of the true location. 22 RPs were used. Although the results are reasonably good, the experiment was not a good indication of a typical indoor setting. There were no people present in the environment and the test-bed was a preselected open space.

Table 2: Probability of device being within 1.5 meters of the correct location for 22 RPs

|  |  |
| --- | --- |
|  | Probability (%) |
| Experiment 1 | 77 |
| Experiment 2 | 83 |
| Experiment 3 | 70 |
| Experiment 4 | 83 |

Li *et al.* [4] experimented with the methodology of the **direction based deterministic approach**. Their methodology suggests that at a static location, the direction (limited to North, South, East and West) that the device’s antenna is facing gives a unique level of signal noise. Their methodology suggests that the mobile user’s orientation has a significant impact on the received signal strength from an access point. This suggestion is easy to prove [4]. The purpose of their experiment was to demonstrate that by recording the signal strength of the mobile device at each AP facing four different directions can improve the accuracy of the localization. The approach naturally requires an excessive amount of man hours in the RP training phase. Their results consisted of 20 test cases where the direction based-based method was correct 95% of the time. They achieved this result by only implementing simple deterministic fingerprinting with directional data included. This should be compared to not using directional data; the localization was correct 55% of the time.

**Section 3 – Comparison of the reviewed techniques**

A table comparing the techniques is attached as Appendix 1. The following characteristics were used to compare the techniques:

Technique Scalability (TS): the degree to which the experiment took place in an area that represented a normal indoor environment. Criteria for this characteristic included:

* the number of APs used for the size of the environment
* the extent to which multiple rooms were covered
* whether people were present in the environment

Cost: What hardware or materials were needed to localize a WLAN node?

Computational complexity (CC): the level of computational performance that was required to execute the technique.

Required training time (RTT): the degree to which the technique needed offline data sampling before localization could be executed. In terms of training RPs, all such offline sampling was considered irrelevant as the number of RPs are always variable.

Static localization performance (SLP): It was difficult to benchmark the static and mobile performance of the different methods, as every experiment was conducted in a unique environment. The numbers of RPs used were consistent for all experiments and the locations of APs were bound to what the environments presented. It is also not directly possible to benchmark deterministic and probabilistic techniques, but for relative purposes the static localization performance for deterministic techniques is the localization accuracy for at most 33 APs. The static localization performance for probabilistic techniques is the probability of the localization error being less than 1.5 meters using 33 RPs.

Mobile localization performance (MLP): The same approach was used as for static localization performance.

**Section 4 – Summery of the experiments and techniques reviewed**

Research done in the field concludes that a WLAN node can be tracked within 1.5 meters with certifiable success. The ability to directly compare techniques based on the exact same environment conditions, such as location of APs and database of RP locations cannot be done with the experiments reviewed. However many different techniques to improve localization error were tested in the above experiments and it cannot go unnoticed that some of these techniques are mutually exclusive. For example, the direction based approach proved that localization error can be lowered by taking into account the direction the node was facing at database training time. There is no reason to exclude real time optimizations such as probabilistic fingerprinting and sensor fusion. The list of techniques and algorithms reviewed can be separated, into mutually exclusive groups as shown in table 2.

Table 2: Mutually exclusive localization performances techniques

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Localization method** |  | **Use of directional information** |  | **Use of sensor fusion** |
| Triangulation |  | Directional RP |  | Sensor fusion |
| Deterministic fingerprinting |  | Non-directional RP |  | No sensor fusion |
| Probabilistic fingerprinting (raw positional result) |  |  |  |  |
| Probabilistic fingerprinting (average positional result |  |  |  |  |

An optimal performance scheme gauged from the experiments reviewed would be probabilistic fingerprinting using the mean result of Bayes’ algorithm over 1 second for RP classification, a database of directionally verbose RPs and sensor fusion. The scheme is shaded in grey in table 2. The combinations of averaging output of Bayes’ algorithm and sensor fusion would result in especially high computational complexity requirements. The training phase would be no longer than with a directional deterministic fingerprinting approach as tested by Li *et al.* [4]. This suggests a new experiment not implemented in the reviewed literature that should be conducted.

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Appendix A: Comparison of reviewed experiments

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **TS** | **cost** | **CC** | **RTT** | **SLP** | **MLP** |
| **Triangulation** | very good | low | low | none | 4-5 m | NA |
| **Deterministic fingerprinting** | Good | low | moderate | moderate | 1.19 m | NA |
| **Probabilistic fingerprinting (static, max probability)** | Bad | low | high | moderate | 77% | NA |
| **Probabilistic fingerprinting (static, mean probability)** | Bad | low | high | moderate | 83% | NA |
| **Probabilistic fingerprinting (mobile, max probability)** | Bad | low | high | moderate | NA | 70% |
| **Probabilistic fingerprinting (mobile, sensor fusion)** | bad | low | very high | moderate | NA | 83% |
| **Direction based deterministic fingerprinting** | good | low | low | high | 95% | NA |

1. Picture adapted from [5] [↑](#footnote-ref-2)