Indoor location estimation using multiple wireless technologies

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Abstract— **Future mobile devices will increasingly have multiple sources of location information associated with them, such as GPS, cellular cell-sector ID, Bluetooth or 802.11 wireless LAN. In fact, cellular phones with GPS receivers and 802.11 wireless LAN are already becoming available. However, not all location technologies will operate everywhere (e.g. GPS typically will not work indoors whereas 802.11 coverage may be available) and they typically have different accuracies and range.**

This paper presents an experimental study of the feasibility of using multiple wireless technologies simultaneously for location estimation. We have collected signal strength information from both IEEE 802.11 and Bluetooth wireless network technologies, developed and applied algorithms for determining location using data for each wireless technology, and then used a simple algorithm for fusing the location estimates from both technologies to try to enhance the accuracy of the location estimates.

I. Introduction

There has recently been a great deal of interest in the development of wireless geolocation techniques, driven not only by their commercial and military potential but also by regulatory pressures, e.g. the need to determine the location of cellular users who originate emergency calls. The proliferation of mobile computing devices and the development of high-speed, low-cost wireless networks has created ample opportunity for geolocation systems, and a large number of techniques have been developed [1], [2]. However, most location systems are developed around specific technologies, and hence are restricted by the limitations of the technology used. This in turn restricts the application set that may be deployed on the system. For example, applications using the Global Positioning System [3] may not be able to function inside buildings due to lack of coverage.

Future mobile devices are expected to have multiple wireless technologies [4]. This will create the opportunity to use multiple technologies to infer the location of a device. This shall not only free applications from the constraints of technology limitations, but also offer applications the flexibility to select and exploit a larger set of location information sources. For example, cell-sector ID may be sufficient to find the nearest taxicab, but finer granularity provided by Bluetooth may be required for locating a user in a shopping mall.

In this paper, we focus on obtaining and fusing data from multiple wireless location estimation sources. In particular, we investigate how location can be estimated in an indoor environment when the user's device has both IEEE 802.11 wireless LAN and Bluetooth connectivity. Clearly other wireless technologies are also candidates e.g. Infra-Red (IR), ultrasound, magnetic pulsing, etc. Our focus in this paper is not on the specific wireless technology per se (although we necessarily have to describe and deal with the problems encountered with our specific technology choices) but the potential use of multiple wireless technologies. We have:

- developed several location estimation algorithms that apply to both technologies.
- used a simple algorithm for *fusing* the location information from both technologies.
- evaluated the performance of both estimation and fusion algorithms in terms location accuracy using experimental measurements.

To our knowledge such an investigation (especially using Bluetooth) has not been previously published in the literature.

The paper is organized as follows. Section II briefly describes related work. Section III provides details on our experimental methodology. In Section IV we describe several simple location estimation algorithms applicable to both technologies, as well as data fusion algorithms that use both technologies together. Section V presents the location accuracy results obtained experimentally. We end with a discussion identifying current limitations and propose further work.

II. Related work

Almost all previous work in this area has focused on estimating user location with a single wireless location technology. Examples of such indoor location systems include the *Active Badge Location System* [5] which uses IR beacons and the *Cricket System* [6] which measures the time-of-flight of ultrasound to estimate distance for indoor environments. Various other systems using RF angulation and lateration have also been developed; see [1], [2] for a survey. More recently, the RADAR system from Microsoft [7], the Nibble system from UCLA [8] and other location systems [9], [10] have also been developed; these are all RF systems that rely on an indoor wireless data network. In principle, location information from any of the location technologies mentioned above could be used to estimate location from multiple technologies. We have used 802.11 wireless LAN and Bluetooth Personal Area Network (PAN) technologies because of their low cost, simple infrastructure and rapid proliferation for providing wireless data services, not just for location information.

Taking advantage of multiple technologies simultaneously to provide improved location estimates was proposed in [11], [12]. However this work provides no details on implementation or experimentation work. We describe specific algorithms for location estimation and fusion and report on detailed

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experimental measurements to evaluate the location accuracy that results.

Like RADAR [7], we use Static Scene Analysis [1] as the location estimation methodology. RADAR is an indoor location tracking system that uses 802.11 wireless LAN as its sensor technology. While our methodology is similar to RADAR, we believe it differs in important details (discussed later) and is much more representative of realistic situations.

Finally, IBM Alamden [13] has focused on resolving conflicts between location information generated from multiple sources. This work proposes an algorithm that sorts location information based on co-location, time stamping and user-device association, to select the information source at the top of the sorted list. On the other hand, we propose a simple algorithm that integrates information from multiple sources for indoor environments using geometric averaging.

III. EXPERIMENTAL METHODOLOGY

This section outlines the method used to collect raw signal data for Bluetooth and 802.11 wireless LAN and discusses the use of Static Scene Analysis to smooth wireless channel effects and translate signal data into location estimates.

A. Experimental Testbed

Our experimental testbed is located on the fifth floor of a six-story building. The experimental area measures 32.2m by 25.7m and consists of Bluetooth and 802.11 wireless LAN infrastructures which provide overlapping coverage.

The Bluetooth infrastructure features three stationary *base stations* (slave devices), and one *mobile client* (master device). The Bluetooth base stations consist of three laptops featuring a Pentium 233 MHz processor and 64MB of RAM. The mobile client is a Pentium 500MHz, 128MB RAM laptop. The base stations and client are installed with Toshiba Bluetooth PCMCIA cards which provide a nominal range of 30m. The Bluetooth base stations are positioned to provide overlapping coverage, and form mutual Bluetooth connections to aid real-time data collection.

The 802.11 wireless LAN infrastructure consists of three Orinoco base stations. The range of the network is nominally 100m. The wireless LAN client consists a Pentium 800 MHz laptop equipped with a Lucent Silver 802.11 wireless LAN card and the Orinoco Client Manager software package.

B. Static scene analysis

Static scene analysis was used as the location estimation technique because it appears to provide good accuracy for location estimates in small and medium sized locales and does not require precise time synchronization between mobile clients and base stations. From the perspective of our approach as a whole, other location estimate techniques, such as those used in Nibble and the CMU system, could also be used.

For Radio Frequency (RF) based technologies, static analysis involves the 1) measurement and storage of *offline* radio signal characteristic (e.g. signal strength) at fixed, known locations in the area of interest e.g. floor in a building, prior to system operation, 2) measurement of *runtime* signal characteristic of an active radio connection of a mobile device during system operation, 3) comparison of offline and runtime data to find one or more fixed floor locations where the offline characteristic is closest to that measured at runtime.

For both 802.11 and Bluetooth we use radio signal strength as the determining radio characteristic in static scene analysis because previous work has shown that it is better suited for location estimation than the signal-to-noise ratio. Nonetheless, radio signal strength can vary greatly temporally as well as spatially. Thus we employ the *bracketing* heuristic to generate location estimates from signal strength: for a given runtime signal strength measurement r the database is searched to find the closest offline measurement in the range $r-b$ and $r+b$, where b is a tunable parameter called the *bracket* (with ties broken to favor stronger signal strengths); if none is found the location is assumed to have insufficiently reliable coverage and the measurement is discarded. Finally, note that a measured radio signal strength from a single base station may result in a set of several *candidate* locations; these candidate location sets are resolved to a single location estimate using the algorithms described in Section IV.

C. Data Collection

To collect offline measurements for static scene analysis an imaginary 2m x 2m grid was placed on a scaled map of the experimental area and used to select 49 different equidistant physical locations on the grid.

1) Bluetooth data collection: The strength of a Bluetooth connection is measured in terms of *link quality* that varies from 0 to 255. Although we would have preferred a measurement in dBm, link quality was the only option offered by the available hardware.

In the offline phase, 50 link quality samples were measured in each of four directions (north, south, east and west), at each of the 49 physical locations, for each of the three base stations. In the runtime phase, raw link quality information was collected at 18 different physical locations. These 18 locations were chosen at random and do not correspond to the grid locations where offline measurements were taken. Also, the measurements were taken at a different time than the offline measurements. *Thus we consider a realistic situation that takes into account both the temporal and spatial variability of wireless links.* We chose 18 locations deliberately so as to systematically cover three different coverage scenarios: at 6 of the locations there was coverage from 3 base stations, and another 6 there was coverage from 2 base stations, and at the remaining 6 there was coverage from only 1. At each location, 50 samples of link quality data were taken while facing the north direction. Note that while the the offline measurements were taken at multiple orientations (north, south east and west), since there is no simple way to detect a mobile user's orientation, they cannot be matched directly to the user's orientation. *Thus we consider the realistic situation where a user's orientation is unknown and offline data is the average of measurements taken with multiple orientations.*

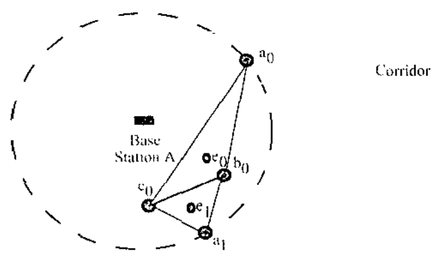

Fig. 1. The diagram shows the formation of polygons (a_0, b_0, c_0) and (a_1, b_0, c_0) where a_0 and a_1 are estimates from base station A, b_0 and c_0 are estimates from base stations B and C respectively. Smallest Polygon searches for the smallest polygon (a_1, b_0, c_0), and returns as an estimate the centroid of the polygon, e_1.

2) 802.11 data collection: The method for 802.11 data collection was similar to that for Bluetooth with the strength of the 802.11 wireless connection measured in terms of *signal strength in dBm*.

IV. Location Estimation Algorithms

As discussed previously, the signal strength measurements for each wireless technology are processed using bracketing. For 802.11 the result is a set of vectors $< x, y, A, B, C >$ where (x, y) is the location of the measurement in the floor coordinate system and A is the set of candidate locations obtained (as a result of bracketing) for the measurements taken of the signal strength from base station A; similarly B and C are the candidate locations obtained for base stations B and C respectively. For Bluetooth we denote the vectors $< x, y, B_A, B_B, B_C >$. Note that depending upon the location where the measurements are taken, any of the candidate location sets may be empty. In this section we describe several heuristic algorithms used to resolve the candidate location sets into a single location estimate.

A. Smallest Polygon (SP) algorithm

The Smallest Polygon algorithm searches through all polygons that can be formed, where each vertex is from a different candidate location set (i.e. one each from A, B, C). We call such a polygon a *distinct-vertex* polygon, and the intention of using such polygons is to allow a fair contribution from all base stations. Smallest Polygon finds the distinct-vertex polygon with the smallest perimeter, and returns the centroid of that polygon. If there is only one non-empty location set (i.e., there is coverage from only a single base station), Smallest Polygon drops the distinct-vertex requirement and selects one of the candidate locations at random. Figure 1 illustrates an example.

B. Triangulation (TN) algorithm

Triangulation is a classical location estimation technique that has been used in various location systems including the widely accepted GPS. Triangulation forms, for each base station, a circle with the base station as the center and passing through a candidate location. If the three circles formed for three base stations intersect at a single location, that location forms the best estimate of the mobile devices' location.

However, frequently circles intersect at two points or do not intersect at all. The heuristic we use to resolve this is that (a) each circle is the largest possible, i.e., where there is a choice of candidate locations to draw a circle for a given base station, we choose the candidate furthest from the base station; and (b) the intersection points belonging to each circle-pair are used to form the shortest distinct-vertex polygon and the centroid of that polygon is used as the final location estimate.

C. Nearest Neighbor (NN) algorithm

The Nearest Neighbor algorithm is used in the RADAR system for 802.11 wireless technology and operates as follows. Assume a triple (a, b, c) where each element of the triple is the runtime signal strength measured for base stations A, B, C respectively. The observed triple is compared with the offline measurements to find the location l with the signal strength triple (a', b', c') such that the Root Mean Squared (RMS) error $r = \sqrt{((a - a')^2 + (b - b')^2 + (c - c')^2)}$ is minimized; that location l is then taken as the mobile device's location estimate.

Observe that Nearest Neighbor always returns a location on the grid where the offline measurements were taken while Smallest Polygon and Triangulation generally almost never do. A modification to Nearest Neighbor evaluated in the RADAR system is to consider not only the location with the lowest RMS error but the locations with the k lowest RMS errors, and average the result. It was found in the RADAR system that the reduction in distance error was small, and beyond $k > 5$ the error actually increased.

We now describe a simple algorithm that processes estimates from individual sensor technologies in a bid to achieve more accurate location estimates.

D. Basic (Averaging) Fusion

Smallest Polygon, Triangulation or Nearest Neighbor may be used to obtain location estimates for individual sensors. Each sensor estimate contributes to polygon formation and the centroid of this polygon is proposed as the final result. In our case, since we have two technologies, we use the midpoint of the line connecting the estimated location obtained for each technology.

V. Performance Evaluation

This section presents results of our experiments. While an extensive experimental evaluation has been carried out, we only present some of the results due to lack of space. We evaluate: (1) how well the estimation algorithms work when using a single technology, and compare them to each other, and (2) how well they work when using multiple technologies simultaneously. In the latter case we compare different scenarios where multiple technologies are used, and the different algorithms when used in those scenarios. The metric used throughout is the mean distance error, where a location estimate, say (x', y') is compared with the known true location (x, y) to yield the *distance error* $e = \sqrt{((x -}$

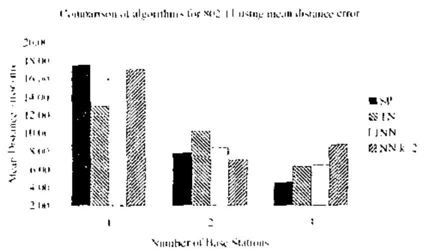

Fig. 2. Average distance error for 802.11 wireless LAN using SP, TN, NN and NN k=2 across one, two and three base station coverage locations.

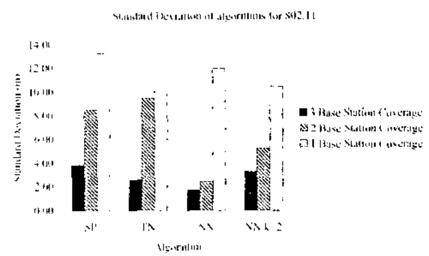

Fig. 3. Standard deviation of distance error for SP, TN, NN and NN k=2 across one, two and three 802.11 base station coverage locations.

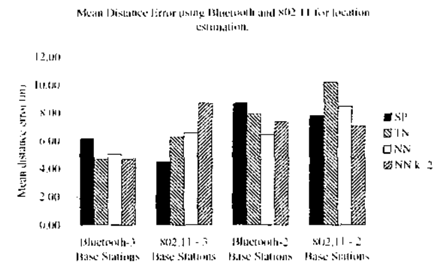

Fig. 4. Mean distance error for Bluetooth and 802.11 using SP, TN, NN and NN k=2 under three and two base station coverage scenarios.

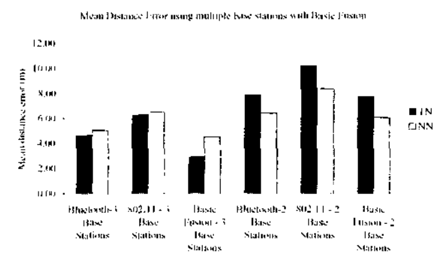

Fig. 5. Mean Distance Error using multiple base stations with Basic Fusion.

$x_j) + (y - y_j))$, and the mean distance error is calculated for several location estimates.

A. Comparison of the location estimation algorithms

Here we briefly compare the location estimation algorithms in terms of mean distance error using 802.11. Figure 2 shows the mean distance error for the different algorithms for locations where there is coverage from 1, 2 and 3 base stations respectively. First we observe that, as expected, in general distance error decreases as the number of base stations covering a location increases. This trend is mirrored in the standard deviation of the distance error in Figure 3. The exception is the NN k=2 algorithm, for which error increases in going from 2 to 3 base stations. In this case choosing more candidate locations (with k=2) causes locations further from the actual location to be included as candidates; with 3 base stations, this effect becomes pronounced.

We also observe that in general the Smallest Polygon algorithm outperforms the other three algorithms when using 802.11, by around 1.8-2m (28%-31%) and 4-5m (24%-28%) for 3 and 1 base stations coverage (for 1 base station coverage SP and TN show equal results because when no circle intersections are found TN falls back to SP). The exception is the case of 2 base stations where NN k=2 performs better than SP, but the improvement is slight and SP remains the best choice overall. However, this improvement comes at the expense of a higher variance in the location estimates.

Figure 4 compares the location accuracy obtained by using Bluetooth and 802.11 individually for varying numbers of *visible* base stations. In general using Bluetooth gives better accuracy than using 802.11 for all algorithms except SP. Thus in an environment offering both 802.11 and Bluetooth base stations, TN or NN would seem to be the better single algorithm for location estimation. Furthermore, these algorithms show smaller standard deviation than SP (not shown due to lack to space). Thus the following discussion focusses on TN and NN.

B. Location data fusion

We now consider the effect of using multiple technologies simultaneously. One of the key advantages of using multiple technologies is that location estimation can take advantage of information that would not be available otherwise. Intuitively, this should improve location accuracy because information is collected from more base stations of different technologies. We quantify this improvement in Figure 5 where Basic Fusion emerges as the winner: for TN the improvement is 1.7-3.3m(36-52%) and 0.2-2.5m(2-24%) for three and two base stations coverage respectively; for NN th improvement is 0.5-2m(10-31%) and 0.4-2.3m(5-28%) for three and two base stations coverage respectively.

We now make a different evaluation of the use of multiple technologies. The total number of base stations is kept constant in all cases, i.e. 3, and different combinations of 802.11 and Bluetooth base stations are used. Figure 6 shows the mean distance error obtained by post-processing the location estimates using fusion. We note that fusion improves location accuracy compared to using 802.11 alone, and this improvement can be substantial - for TN the improvement approximates at 0.6-0.7 m (12-16%) and for NN at 0.4-1.5m (6-22%). On the other hand, the distance error compared to Bluetooth increases to 0.9-1m (19-23%) and 1m (21%) for TN and NN respectively.

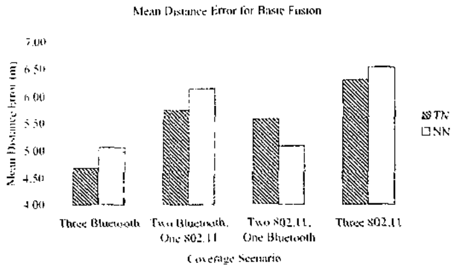

Fig. 6. Distance error for Basic Fusion under varying base station coverage scenarios.

We also note that the results are not unambiguously in favor of using Bluetooth over 802.11. For example, the combination of using two 802.11 and one Bluetooth base stations provides better accuracy (1.1m,17%) than using two Bluetooth and one 802.11 for NN. This indicates that although Fusion with data from Bluetooth base stations generally improves accuracy, the amount of improvement can vary, and the availability of Bluetooth in lieu of 802.11 does not always result in improvements.

VI. Discussion and Further Work

In this section we briefly discuss some of the issues arising with the use of multiple technologies in the light of our experimental observations.

Our experimental methodology is similar to that used in RADAR, but with important differences. RADAR tested the accuracy of the NN algorithm by comparing an offline signal data with all offline measurements. In contrast we take into account the real variation of radio signals in space and time by taking actual runtime measurements, at a different time and at random locations not on the original grid.

We expected relatively better accuracy from Bluetooth than 802.11 than we actually obtained, considering the difference in cell radius for the two technologies. We hypothesize this is due to our use of the first version of Bluetooth PCMCIA cards available in the market. The card did not provide a true signal strength indication (in dBm) but a scalar representation of strength called link quality, which has no units. It is not clear how accurately link quality reflects signal strength. We also found that the Bluetooth link quality measure fluctuates far more than 802.11 signal strength even at a single location.

A direction for future work is to evaluate different radio characteristics for location estimation (e.g. signal-to-noise ratio in conjunction with signal strength, the probability distribution of signal strength, angle of arrival, etc.). Also, more sophisticated location estimation algorithms, both for a single technology as well as for data fusion, should be developed. Finally, the effect of using other technologies together (e.g. IR, ultrasound, GPS, cellular, etc) in indoor as well as outdoor environments should be investigated.

VII. Conclusion

We have carried out a detailed experimental study of the feasibility of using multiple wireless technologies for location estimation. We conclude with the following observations from our study:

- In general Bluetooth gives better accuracy than using 802.11 wireless LAN the algorithms. In an environment offering multiple technologies, Triangulation and Nearest Neighbour work well with Bluetooth. On the other hand Smallest Polygon is found to work well with 802.11 wireless LAN at the cost of higher variance.
- Collecting signal information from multiple technologies implies data availability from an increased number of base stations that should improve location accuracy. We quantify this improvement showing that it can be significant, resulting in improvements of 0.2-3.3m. Thus in an absolute sense exploiting multiple technologies wherever available is beneficial.
- In contrast to the above case, we investigated the impact of fusion on location accuracy with a constant number of base stations from multiple technologies. While our results are not unambiguous, we note that fusion improves location accuracy over the sole use 802.11 wireless LAN by 0.4-1.5m.

In further work we propose considering more sophisticated estimation algorithms for single technology estimation as well as location estimation by fusing information from multiple technologies.

VIII. Acknowledgements

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