Building on CLS: A multi-modal cooperative location-sensing system using Bluetooth and IEEE802.11

(Msc Thesis)

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Abstract

During the last years we witnessed an increasing interest in pervasive computing systems and applications. There is a growing need for systems that will enhance the information access without any distractions to the user. These pervasive systems are embedded to the environment and can offer context- or location- aware services. For the support of these services, location-sensing systems are critical.

One such system is Cooperative Location Sensing (CLS) system. It allows devices to estimate their location in a self-organizing matter without the need for extensive infrastructure, or specialized hardware. The initial CLS version runs on IEEE802.11-enabled devices. We have extended CLS to take advantage of the Bluetooth wireless communication technology. The CLS-bluetooth client uses signal strength information to produce a position estimation. In addition, this extended CLS allows the synergistic use of the two wireless technologies, namely IEEE802.11 and bluetooth.

In this M.Sc. thesis, we analyze these CLS extensions and present the performance evaluation experiments for both Bluetooth-only and joint Bluetooth-IEEE802.11 positioning estimations. Furthermore, we investigated the impact of physical obstacles (mobile or stationery) on signal strength information and on the performance of the system. We found a median location estimation error of 1.7 meters using Bluetooth-only estimation and a median location error of 1.6 meters using the joint IEEE802.11-Bluetooth estimation, under normal conditions.

Περίληψη

Τα τελευταία χρόνια γίναμε μάρτυρες μιας αύξησης του ενδιαφέροντος για pervasive computing συστήματα και εφαρμογές. Έχει δημιουργηθεί μια ανάγκη ενίσχυσης της πληροφορίας χωρίς αυτό να προκαλεί σύγχυση στο χρήστη. Αυτά τα pervasise συστήματα ενσωματώνονται σε περιβάλοντα ώστε να προσφέρουν υπηρεσίες βάση περιεχομένου και χώρου. Τα συστήματα εύρεσης θέσης αποτελούν κρίσιμα μέρη αυτών των υπηρεσιών

Ένα τέτοιο σύστημα είναι το Cooperative Location Sensing (CLS). Το CLS επιτρέπει σε συσκευές να υπολογίζουν την θέση τους στον χώρο χωρίς την ανάγκη εκτενούς υποδομής, ή εξειδικευμένου hardware. Η αρχική έκδοση τουCLS τρέχει σε συσκευές που υποστηρίζουν επικοινωνία μέσω IEEE802.11. Επεκτείναμε το CLS ώστε να εκμεταλλεύεται την τεχνολογία ασύρματης επικοινωνίας Bluetooth. Το CLS βασισμένο στο Bluetooth χρησιμοποιεί πληροφορία ισχύς σήματος για την εύρεση θέσης. Επιπροσθέτως, η επέκταση στο CLS επιτρέπει εύρεση θέσης από δύο ή και παραπάνω ασύρματες τεχνολογίες, στην ίδια συσκευή, συνεργατικά. Αυτή η επέκταση παράγει χωρική πληροφορία βασισμένη στην εύρεση θέσης από διαφορετικούς σχηματισμούς (Bluetooth , IEEE802.11) του ίδιου συστήματος.

Στην παρούσα εργασία αναλύουμε αυτές τις επεκτάσεις στο CLS και παρουσιάζουμε τα πειράματα αξιολόγησης της απόδοσης, τόσο του υπολογισμού βάση Bluetooth, όσο και του συνεργατικού υπολογισμού. Επιπροσθέτως, ερευνούμε το κατά πόσο επηρεάζουν τα φυσικά εμπόδια (κινητά ή σταθερά) την ισχύ του σήματος που χρησιμοποιεί το σύστημα, καθώς και την απόδοση του ίδιου του συστήματος. Τα πειράματα έδειξαν

ότι το σύστημα έχει μέσο λάθος 1.7 μέτρων στον υπολογισμό βάση του Bluetooth και 1.6 μέτρα στον συνεργατικό υπολογισμό. Επίσης διαπιστώθηκε μια μικρή απόκλιση της ισχύς σήματος καθώς και στην απόδοση του συστήματος. Κάτω από ιδανικές συνθήκες χωρίς φυσικά εμπόδια το μέσο λάθος ήταν 1.5 μέτρα για τον υπολογισμό βάση Bluetooth και 1.3 μέτρα για τον συνεργατικό υπολογισμό.

Ευχαριστίες

Η ολοκλήρωση αυτής της εργασίας δεν θα ήταν δυνατή χωρίς την συμβολή πολλών ανθρώπων τους οποίους θα ήθελα να ευχαριστήσω. Πρώτο από όλους θα ήθελα να ευχαριστήσω τον Κώστα Βανδίκα του όποιου η βοήθεια ήταν πολύτιμη. Οι συμβουλές του σε τεχνικό και οργανωτικό επιπέδο κατέστησαν την ολοκλήρωση αυτής της εργασίας δυνατή. Θα ήθελα επίσης να ευχαριστήσω την Λητώ Κριαρά για την βοήθεια της στο MATLAB καθώς και τα παιδιά στο ¨κλουβί' για την φιλοξενία του Hotspot. Θα ήθελα να ευχαριστήσω την ακαδημαική μου σύμβουλο, επίκουρη καθηγήτρια, κα. Παπαδοπούλη για τίς γνώσεις που μου προσέφερε καθώς και για την ευκαιρία που μου έδωσε να δουλέψω σε μια τόσο ενδιαφέρουσα και απαιτητική εργασία. Θέλω να ευχαριστήσω τους συνεργάτες μου στην Cytech και στην Bluebird (Πασχάλη, Στέλιο,Γιώργο, Βάγγελη και Μαρία) για την υποστήριξη τους. Θέλω να ευχαριστήσω ιδιαίτερα την αδερφή μου Νάνσυ, την Αλεξάνδρα και τον αδέρφο μου Μιχάλη για την στήριξη τους και την δύναμη που μου έδιναν όλα αυτά χρόνια.

Τέλος θέλω να ευχαριστήσω όλα τα παιδιά σε όλα τα πανεπιστήμια και στους δρόμους όλου του κόσμου που πιστεύουν οτι η γνώση είναι δικαιώμα όλων και αγωνίζονται για πραγματική, ουσιαστική και ελευθερή παιδεία. Η συμβολή τους στην ακαδημαική κοινότητα αλλά και στην κοινωνία είναι μεγαλύτερη από όσο θα μπορούσε ποτέ να είναι οποιδήποτε επιστημονική έρευνα.

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Chapter 1

Introduction

The last few years we witnessed a burst in technological advances in communication systems. The wireless networking capabilities of mobile devices enable them to communicate with other mobile devices and networking infrastructures so the users can enjoy a variety of services. These advances created the need for synergistic technologies and systems so that services can be provided in different context in totally transparent, to the user, manner so that he/she can perform his/her tasks without any distraction. This is the aim of pervasive computing; to create systems embedded in the environment and enhance the information access in a non distracting manner.

Location-aware systems can provide the user with relevant enhanced information, or other services depending on the location of the user. For example a totally transparent location-aware printing system would allow the user the print his document from the, physically, nearest printer without the need for configuration and without the user taking any action, other than requesting for a print. The system would have to estimate the user location and select the most suitable printer being totally transparent to the user.

Location estimation is becoming a critical since many applications need to provide, higher quality, location-based, services to mobile users. Navigation systems for vehicles, content-rich media services coupled with geographical information, information systems for public places are just some of the possible application of location-aware systems.

The most popular outdoor positioning system is GPS[27] that is used in the majority of military and commercial applications. On the other hand there have been several approaches on the problem of indoor location estimation. These approaches can be classified depending on their ability to operate without infrastructure, harware used, system properties the positioning representation and other parameters. For example some location systems require specialized hardware such as ultrasound emitters to operate and on the other hand, other systems require normal IEEE802.11 networking capabilities. Some require tidious setup process and maintenance through specialized tagging of devices and on the other hand, some systems do not require any setup, or training phase.

1.1 Challenges

There have been several approaches to estimate the position[8, 22, 28] depending on various parameters, such as application requirments,specialized hardware and architecture. In addition, certain technologies and methods are more vulnerable than others. In RF based systems, for example, signal propagation and interference can cause incorrect positioning due to deviation from expected values. Thus, the positioning system should be able to handle the problems that arise with different environmental conditions. Another important parameter to location estimation system is the cost of deployment, maintenance and use. As was the case with specialized hardware if the system is expensive to maintain and deploy that causes practical implications in its everyday use.

1.2 Motivation

We aim to build a location-sensing system for mobile computing applications that can provide position estimates, within a few meters accuracy, without the need of specialized hardware and extensive training. Instead, it will take advantage of the available communication infrastructure. Our location-sensing system should operate both on indoors and outdoors environments.

In addition, we aim that our location sensing system will be able to take advantage of multiple wireless communication technologies present in mobile devices so that it is deployable in devices with different wireless communication capabilities, or even to use more than one communication modules simultaneously to enhance its performance. Multi-modal location sensing systems is an approach that has not been explored in the relevant literature.

1.3 Thesis statement

This thesis is based on *Cooperative Location Sensing System* (CLS)[17]. It is a location sensing system that does not require extensive infrastructure or specialized hardware and can take advantage of existing wireless communication infrastructure. CLS enables devices to cooperate with each other in a self organizing matter. It incorporates a grid-based terrain representation so it can incorporate external information from other systems such as GPS.

CLS is easy and cost effective to be deployed and maintained, yet it remains competitive in its accuracy compared to the best published results on location-sensing in mobile computing. It was designed by M. Papadopouli and H. Fretzagias. Prior to this work existing implementation could take advantage of IEEE802.11 infrastructure to produce estimations[35, 21]. This thesis extends CLS implementation so that it can take advantage Bluetooth infrastructure and be deployable in Bluetooth-enabled devices. In addition this extension enables CLS to produce a joint estimation, using simultaneously both IEEE802.11 CLS module and Bluetooth module, with enhanced performance.

To evaluate the extended CLS we performed experiments. We found a median location error of 1.7 meters using Bluetooth estimation and a location error of 1.6 meters for joint estimation. The performed experiments were conducted under two distinctive environment conditions to evaluate its performance in different environments. In addition we investigated the impact of physical obstacles(mobile, or stationary) on the system and on the signal strength measurements obtained by the system.

1.4 Thesis outline

The present thesis is organised as follows:

- **Chapter 2:** This chapter presents a categorization of location estimation systems based on several characteristics. In addition, the most important location-sensing techniques used are presented.
- **Chapter 3:** This chapter presents the most representative location sensing systems and their methods of estimation.
- **Chapter 4:** In this chapter, we describe the location estimation method of *Cooperative Location-sensing System* (CLS). In addition we present the Bluetooth subsystem and the algorithm responsible for the joint IEEE802.11-Bluetooth estimation.
- **Chapter 5:** In this chapter we present the experiments to investigate the performance of the proposed system. We analyse the experiment setup and various properties of the system and present the results. In addition we investigate the impact of physical obstacles on the performance of the system.

- **Chapter 6:** In this chapter we compare our work with the most representative location-sensing systems that are referred in the related work (Chapter 3).
- **Chapter 7:** In this chapter, we discuss our main conclusions and future work plans.

Chapter 2

Background on location sensing

In order for a location sensing system to calculate a position of a mobile device it needs to gather certain information. It then needs to process this information, put into a certain meaningful context, in order to estimate a probable position. Each environment offers various resources of information that a location sensing system can exploit for its calculations. Each resource of information has distinctive characteristics and thus there are different types of systems that each of them utilizes certain fragments of the available resources. In addition the precision of the position estimation depends on various other factors that the system has to take into consideration in order to produce an estimation.

As it was mentioned above location sensing systems can utilize various information resources in order to produce an estimation. Depending on the resource of information and other characteristics, such as the hardware, used we can classify location systems in various categories.

2.1 Metrics and methodology

Location sensing systems can be classified according to the method that a radio frequency can be conducted and include systems that use the following metrics:

- Received signal strength indication (RSSI)
- Direction resolve (Angle of Arrival)
- Distance resolve (Time of Arrival, Time Difference of Arrival)

The signals that are going to be used in the localization process, in each of the above systems, could be either radio frequencies (RF) from the IEEE 802.11 wireless network, infrared (IR) or ultrasound.

2.2 Systems based on signal strength

The Received signal strength indication (RSSI) is a measurement of the strength (not the quality) of the received signal in a wireless environment, in arbitrary units. Location sensing systems[20, 3] that take advantage of signal strength information of the received signal, either use a probabilistic on the location[24, 37], or use a known mathematical model which describes the path loss attenuation of the signal with distance[33]. In the first case a model can be used to make predictions about the location associated with a set of new signal strength data. Building such a model involves the construction of a probability function from a histogram of training data which estimates the probability that a particular measurement corresponds to a particular location on the area profile. In the second case the measurement of signal strength provides a distance estimate between the mobile object and the base station. Consequently, the mobile object must lie on a circle which has as a center the base station and as radius the distance between them. The distance can be measured by calculating the path loss. The path loss can be found if the mobile object knows the power transmitted from the base station and the received power.

2.3 Systems based on distance

A common method followed by systems that are based on distance is lateration[19]. Using lateration the system computes the position of the object by measuring its distance from multiple reference points. In order to estimate the position of the object in 2 dimension the method requires 3 reference points(figure 1). For 3 dimensional estimation the system requires 4 reference points. There are 3 different approaches in measuring distance:

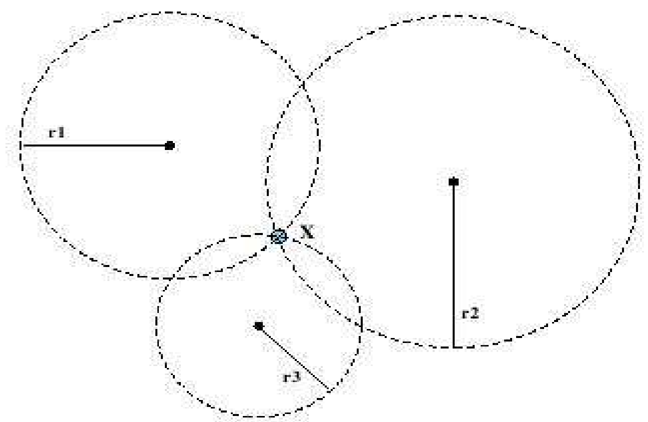

Figure 1: Position estimation based on lateration. Distance measurements of 3 non-collinear points is required.

- Direct. Measurements of this category require a physical action or movement in order to produce usable information. For example robots use the odometry technique in order to know what distance they have covered to estimate their position relative to previous know position.

- ToA. The systems that belong in this category estimate the position by measuring the distance the device has from base stations. In most occasions in order to calculate the distance the system measures the Time of Arrival(ToA) of the signal. ToA is the time needed for one way propagation of the signal with a known transmission speed. In order to resolve any ambiguities at least

3 base stations are needed. In order to produce the estimate synchronization between the mobile object and the base station is needed so there is a common time reference. In addition another technique would be to synchronize the base stations and the mobile object would calculate not the time ToA but the difference of each base station ToA, Time Difference of Arrival(TDoA). An example of such system is GPS where satellites are precisely synchronized with each other so the receiver device can calculate the distance based on the TdoA.

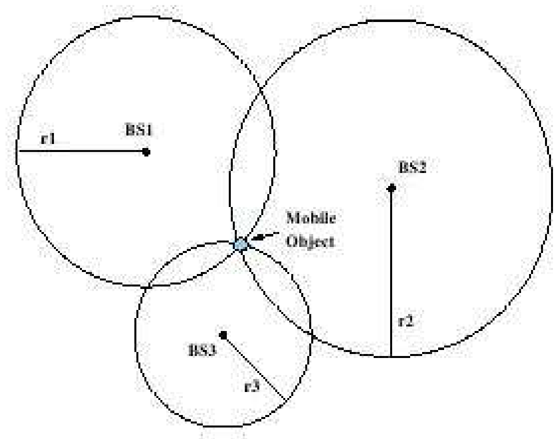

Figure 2: Estimation based on ToA

We mentioned above systems that are based on signal strength. There is a method for location estimation that utilizes signal strength information in order to produce distance information. This method is attenuation and is based on the fact that intensity of the transmitted signal decreases as the distance increases. So based on the signal strength of the received signal the system calculates the distance it has traveled in order to produce location estimation. This technique though, is not very accurate in environments with obstacles such as offices, or laboratories because the signal will weaken due to these obstacles and other factors besides distance.

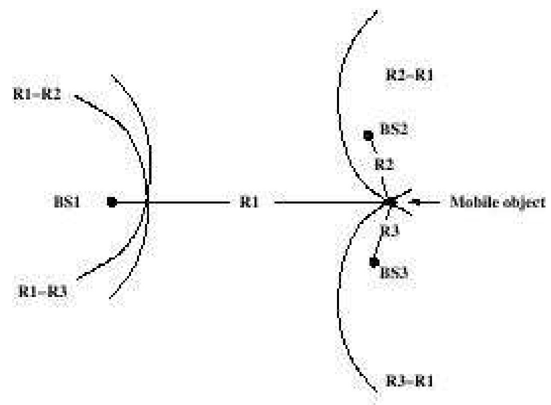

Figure 3: Estimation based on TDoA

2.4 Systems based on direction

These systems base their estimation on measuring the Angle of Arrival (AoA) of a signal[26]. In order to estimate the position they refer the measured AoA coming from an base station to a reference axis. The intersection of lines created by the signal angle from the base stations is the estimated position of the node. This technique can suffer from reflected signals though that the receiver node can confuse as bcleanb signals coming from a base station. This is more frequent in non line-of-sight(LOS) but multipath effect is still present in LOS were the multipath will still interfere with the angle measurement. The accuracy of the such systems diminishes diminishes with increasing distance between the mobile object and the base station due to limitations of the devices used to measure the AoA. In grid based testbeds this technique gives good results when it is used in macrocells, since the signals arrive with a relatively narrow AoA spread at the base stations in contrast to microcells.

Angulation is similar to lateration that we mentioned above but instead of distances it uses angles to determine an objectbs position. In order for a system that uses two dimensional angulation to estimate the position of an object it requires two

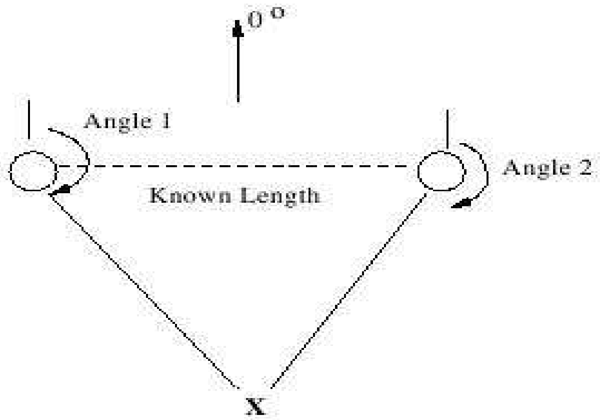

Figure 4: Position estimation based on angulation. It requires 2 angle measurments and 1 distance measurement.

angle measurements and one length measurement, such as the distance between the reference points(figure 4). For three-dimensional angulation , a precise position can be computed using one length measurement, one azimuth measurement and two angle measurements. In some cases for convenience in implementation a constant reference vector is used, such as the magnetic north.

2.5 Scene analysis

Systems that take advantage of this technique[23, 4] rather than use emitted radio signals use features of a scene observed from a particular vantage point to produce an estimation about the location of the observer. In static scene analysis, features of a certain scene are looked up in a predeoned dataset and are correlated with certain object locations, much like signal strength information is matched with training phase signal strength sets from certain know locations. In contrast, differential scene analysis tracks the difference between successive scenes to produce an estimation. Differences in features of the scene will correspond to movements of the observer. The scene itself can consist of visual images, or any other measurable physical phenomena, such as the electromagnetic characteristics that occur when an object is at a particular position and orientation.

The advantage of scene analysis is that the location of objects can be inferred using passive observation and features that do not correspond to geometric angles or distances. The disadvantage of scene analysis is that the observer needs a rather large dataset of correlated features with positions in the environment against which it will compare its observed scenes. Furthermore, changes to the environment in a way that alters the perceived features of the scenes(such as lighting conditions in visual scenes) may necessitate reconstruction of the predeoned dataset or retrieval of an entirely new dataset.

2.6 Proximity

The proximity technique measures nearness to a known set of points. There are three general approaches to sense proximity:

- Detecting physical contact. Technologies for sensing physical contact include pressure sensors, touch sensors and capacitive oeld detectors.
- Measuring wireless cellular access points. Another implementation of the proximity location technique is monitoring when a mobile device is in range of one or more access points in a cellular network.
- Observing automatic ID systems. A third implementation of the proximity technique uses automatic identification systems, such as credit card point-of-sale terminals, computer login histories, land-line telephone records and electronic card lock logs.

2.7 Hardware and architecture

We categorize systems based on the hardware they are using to gather the required information in order to produce an estimate of location.

- Specialized hardware: These systems are tightly connected to specialized hardware (such as tags, cameras, ultrasound receivers) to locate a wireless device.
- Non-specialized hardware: There are location-sensing systems that have no need of a specialized hardware. In stead their measurements are based on existing infrastructure, such as the IEEE 802.11 infrastructure.

In addition we can categorize systems based on they operational architecture.

- Systems based on infrastructure: Systems in this category take advantage of their environmentbs infrastructure. For instance, a system can receive position information from an access point which is wired connected with the Internet.
- Ad-Hoc systems: An ad-hoc network has no infrastructure, and the nodes taking part form an arbitrary topology. The network nodes are free to move randomly and organize themselves arbitrarily. Such a network may operate in a standalone fashion. In a purely ad-hoc location sensing system, all of the objects estimate their locations by cooperating with other nearby objects taking part on the network. The estimated location can be either relative to other objects or absolute if certain objects participating on the network have know position.

2.8 Position description

Another categorization of location sensing systems is based on how they describe the position[31].

2.8.1 Psysical vs. symbolic

From the point of view of the type of information available, location-sensing systems can be characterized as either physical or symbolic.

- Physical : Physical information provides the position of a location on a physical coordinate system, for example global coordinates.
- Symbolic: Symbolic information employs textual descriptions of location (and may be either geographic symbolic, or place symbolic), for example *b*next to coffee room*b* .

2.8.2 Absolute vs. relative

Whether physical position or symbolic location is used, the information provided may be either absolute or relative.

- Absolute: Absolute position implies a location system that employs a shared reference grid for all located objects, for example latitude, longitude and altitude.
- Relative: A location system that uses relative positions can have a distinct frame of reference, for example b2 meters from network printerb.

The distinctions along the absolute/relative and physical/symbolic categorization are not inherent system capabilities but rather abstraction for the identification of the types of information available at a certain system. They also have significant repercussions for deducing derivative and higher-level spatial attributes; for example orientation (Which way is the object moving), velocity (how fast fast is the object moving) and connectedness (Is there a way to get from point A to point B).

In many cases it is possible to transform one type of information to another. For that to happen though in most cases another piece of information needs to be available. For example it is possible to move from relative position to absolute position; knowing the absolute position for a certain point in a relative system, any point of that system given its relative position can be transformed to absolute.

2.9 Infrastructure location

In addition further categorization can be made based on the location of the infrastructure of the location sensing system.

- Terrestrial : The terrestrial systems(e.g., reference base stations) are placed on the ground.
- Satellite: Satellite location systems use satellites as reference points to calculate positions accurate to within meters. The most popular satellite based location sensing system is the Global Positioning System (GPS)[27], which is described in the following chapter.

Depending on whether the measurements take place locally or remotely, we can classify the location-sensing systems into two categories:

- Auto-localization systems: In these systems, the measurements are taken place in the device that is to be localized itself, as in GPS.
- Remote localization systems: In remote localization systems, the measurements are taken place in a different place other than the device that is to be localized.

In addition, we can further categorize systems depending on whether they require infrastructure[8, 28, 22, 16], or are ad-hoc[32, 25, 12, 38, 13, 15].

2.10 Accuracy and precision

In order to evaluate the performance of location sensing systems we need to not only its accuracy, but its precision as well[31]. Accuracy is the property that represents the smaller distance estimation error the system can produce from the actual position. Precision is the percentage of time that the system achieves the prescribed accuracy. Only using on of those properties does not suitably desribe the performance of the system since only taking into consideration accuracy we do not have enough information as to how often such accuracy is going to be achieved. In certain occasions, it is possible despite the methodology followed by the system, to increase these properties by tuning the system according to the environment, or increasing other parameters, such as the available reference base stations.

2.11 Summary

In this chapter we examined various location sensing techniques and various properties of location sensing systems (table 1). This taxonomy is based on properties such as the metric according to which the estimation is made. There are location sensing systems that base their estimation on signal strength and others on time of arrival, or angle of arrival. In addition location sensing system can be characterised based on their architecture (infrastructure vs. ad hoc) and if they require specialzed harware. In the case they require infrastructure further categorization can be made according to the location of the infrastructure. Another property that we should consider is the distinction between absolute and relative location even though this distiction is not an inherent system cabapibility it, abstractly identifies information of a certain system.

Classification	**System property**
metric type	SS, AoA, ToA, TDoA
architecture / hardware	Infrstracture vs. ad hoc, specialezed vs. non-specialized hardware
infrastructure location	auto-localized vs. remotely localized, terrestrial vs. satellite
position description	Psysical vs. symbolic, absolute vs. relative

Table 1: Taxonomy of location sensing systems.

Chapter 3

Related work

3.1 Bluetooth-based systems

Some systems take advantage of the Bluetooth technology to estimate position. This does not limit these system in adopting a certain aproach. There are Bluetooth-based location-sensing systems that use the signal strength aproach, other that require specilized hardware and others that use the distance-based estimation aproach. For example, *Spreha*[22], requires special Bluetooth tag devices to locate objects and on the other hand *Indoor Bluetooth-based positioning system*[16] takes adantage of RSSI information to calculate the position. In the table 2 below you can view a taxonomy and accuracy information of these systems. *BIPS*[11] and *Spreha* do not estimate absolute poistion but rather produce a relative position. On the other hand, *Indoor Bluetooth-based positioning system* uses a grid based aproach to produce absolute positions. In the following sections these systems are presented in detail.

	Metric	Architecture	spec. hardware	position
System a	RSSI	centralized	no	absolute
System b	RSSI / Time Of Flight	centralized	yes	relative
System c	Bluetooth inquiry time	cetralized	no	relative
System d	RSSI	hybrid	no	absolute

Table 2: Bluetooth-base location estimation systems: a) Indoor Bluetooth positioning system, b) Spreha, c) BIPS, d) In-building location using Bluetooth

3.2 RSSI based systems

3.2.1 Smart Space

The system utilizes the Receiver Signal Strength Indicator(RSSI) module implemented in bluetooth antennas, to measure the connection signal strength and estimate the location of a bluetooth enabled device. The key design goals of the system were acceptability, low power consumption and low cost [9]. The system is based on multiple antennas access points. Each antenna is located in a different place on the same location in order to obtain a different measurement of the RSSI. A key mechanism of the measurement is that the connection with the mobile device is kept open and used by the different antennas, in a 'round robin' way, to avoid the 3 seconds overhead of opening the connection with each individual antenna. To solve the problem of the difference in analogy of RSSI and signal strength they used attenuators for each antenna and thus they changed the granularity of the signal for each antenna allowing them to obtain different measurements for different distances. The system is simple and inexpensive in its installation and operation. From the other hand it requires configuring the attenuators which is an extra overhead besides the training.

3.2.2 Indoor Bluetooth-based positioning system

The system utilizes bluetooth wireless connectivity technology and a triangulation method in order to produce the location estimation[16]. Because of bluetooth limitations and possible reflection of signal indoors the authors could not directly use RSSI values to produce distance values. The solution proposed by the system is to obtain RSSI measurements from various distances in a fixed indoor location and then based on the RSSI measurement of the system, produce the distance values. The measurements are not obtained by the beacons rather from the Bluetooth-enabled PDA which connects to each of the beacons and obtains the RSSI measurement. It then, based on the training phase, calculates the distance and computes its location based on the triangulation algorithm.

Even though the system works with relative accuracy its has its limitations. Most bluetooth enabled mobile devices such as cellular phones do not provide the RSSI module and thus there is no way to obtain measurements from that device. In addition many mobile devices have limited processing capabilities. However, because the mobile device is responsible for the calculations, the system is decentralized and respects users' privacy and that is a major advantage over other systems.

3.2.3 In-building location using Bluetooth

Another approach was made by Miguel Rodriguez, Juan P. Pece and Carlos J. Escudero of the University of Coruna[30]. The system utilizes Bluetooth wireless connectivity technology to produce the location estimation. One of the system's main design goals is its architecture to be independent from the algorithm used for location estimation. The system provides the underlying system components and communication mediums but the researcher is free to use any algorithm he wishes to perform the estimation such as triangulation or scene analysis.

The system consists of mobile devices ,access points and the server. In order for the system to work a training phase is required. During the training, the mobile device estimates the RSSI value with each of the access points for a known location and the correlation of RSSI value along with the location is stored for future reference. During normal system operation, the mobile device estimates the RSSI value of the connection with the access points and makes a request for location estimation to the server. The server takes the RSSI values obtained by the mobile device and based on the stored correlation information and the estimation algorithm used, it estimates the location of the mobile device and sends back the information.

The fact that the calculation is not done by the mobile device is an advantage over systems that the calculations are performed by the mobile device which most probably has limited processing resources. In addition the system takes a hybrid approach on how centralized is its architecture. Even though a central server estimates the location the request for the estimation is client initiated. Another advantage of the system is that its architecture is independent from the estimation used so it can accommodate various mechanisms depending on the location or the deployment requirements and in addition be a solid platform for evaluating various algorithms.

3.2.4 Spreha: A PlaceLab Inspired Location System for Sentient Artefacts

The system is an attempt to design and implement a location sensing system, based on Place Labs' initiative of RF/WiFi reference point-based location sensing, using Bluetooth technology[22]. The authors of the system stress that for indoors a location sensing system's flexibility and simplicity is more important than accuracy, so they set those to be their design goals. They considered accuracy with error of even a few meters to be acceptable. They justify that by saying that such systems would be used for contextual services so an accuracy of centimeters is not needed. The goal of the design was to implement a system that works in a similar way to GPS so both system can work together when user is roaming from indoors to outdoors.

The System consists of different components that work together and coexist in the same location to produce a location estimation. The authors divide the components in hosts, artifacts, agents and a location manager. The location manager is responsible for informing other components about their location and the location of other components. The system estimates the whereabouts of a component based on what other components can bseeb. The static hosts such as cabinets or mirrors have bluetooth tags on them and act as a static references whereas other components, the mobile artifacts, such as lamps can change location and thus have to reevaluate their position. The agents run on mobile devices that roam the location, constantly changing positions. The estimation is based on the RSSI and Time Of Flight(TOF) of the connection with other static or mobile artifacts. The various artifacts inform the manager about other artifacts or mobile devices in their proximity periodically. The location manager has to resolve conflicts between different artifacts that all bseeb the device in their proximity based on RSSI and TOF.

The system achieves the goals of flexibility and simplicity as no complex algorithms or extensive training is required. A drawback of the system is that, depending on the deployment it might be expensive to tag many components to use as static or mobile references. In addition it is a large task to input so much information for the location. However this has to be performed only once and even if artifacts that the system considers to be mobile change place, the system adapts to the changes, unlike other systems that in a similar case would require additional training.

3.2.5 RADAR

RADAR[8] is an RF-based location sensing and tracking system. It is one of the first location sensing systems to utilize IEEE802.11 technology. The system utilizes the signal strength information of the connection between the base stations and the mobile device and then by means of triangulation it estimates the location of the mobile device. The authors investigated the use of signal to noise ratio instead of signal strength but their experiments showed that signal to noise ratio is not a reliable metric. This is due to the fact that noise has random fluctuations and thus it can not be used. For their experiments they deployed various base station equipped with wireless Lan cards in the second floor of a 3 story building. In addition as a mobile device they used a laptop equipped with a wireless Lan card. They constructed a map of the floor and during the training phase the user indicated where in the map he/she was. In addition to the indication on the map the based stations obtained synchronized measurements of the signal strength of the connection with laptop. Using the signal strength data and the traces of the user the authors build the map of the floor with the corresponding signal strengths. In order to determine the location the authors consider two approaches;the empirical method where they used the correlated data from the training phase and the signal propagation modeling method.

They authors investigated various techniques to improve the accuracy of the empirical method. They performed experiments that showed that the user orientation plays an important part in the signal strength indication and should be taken into consideration when estimating the location. In addition they investigated the importance of he number of the number of sample locations and the number of samples taken from each location They discovered that the greater the number of sample locations the greater the accuracy. But after a certain number the accuracy does not increases neither though decreases(after 40 in their testbed). In addition they discovered that a moderate number of samples per location(3 in their experiments) is enough for the estimation.

The second method the authors considered was the signal propagation model method. Instead of training the system supplying the estimation algorithm with a dataset of signal strength correlated with location they tried to estimate the signal strength of the connection in various distances. This holds the advantage of not having to train the system for each location making it easier to deploy.

3.3 Distance based systems

3.3.1 The Cricket location-support system

Cricket[28] is a location sensing system that allows applications to know their physical locations by means of listeners on the mobile devices. Beacons are deployed in a location and the listeners on static or mobile nodes pick the information transmitted by the beacons to determine their location. The authors. One of the basic design goals of the system was to develop a decentralized system that respects the privacy of the users. The authors emphasize that their goal was a location support system rather than a location tracking system that stores user information on database. The system is not expensive as each cricket device costs no more than 10 dollars in commodity hardware and is easily deployed as the only thing to be set in a beacon is a string describing the location.

The beacons are positioned on walls or on ceilings and transmit an RF and an ultrasound signal. Location information(the string that describes the location) is obtained from the the RF signal and the the listener estimates the distance from the beacon by the difference on the time of arrival of the ultrasound signal with the RF signal coming from the same beacon. In order to avoid persistent collisions of different beacons transmitting simultaneously the authors used randomization due to the fact that th system is decentralized so there cannot be any explicit coordination between the beacons. In addition to minimize errors due to collisions of signals the authors suggest two methods; use a relatively sluggish transmission rate of RF signal and listener inference algorithms.

The authors, through various scenarios, proved that the listener can successfully correlate the RF and the ultrasound signals coming from the same beacon. Estimating the distance from one signal might lead to errors because this signal might be reflected so a greater number of samples is need to to securely estimate the distance. The authors suggest the use of minMode algorithm. They compute the per-beacon statistical modes over the past n-samples. Then for each beacon the listener picks the distance corresponding to the mode of distribution and uses the beacon with the minimum distance value. In order to avoid using the approach of a more centralized system to allow a listener to successfully choose a beacon and overcome physical boundary problems the authors suggest proper positioning of the beacons in the same distance from a physical boundary (for example, same distance from a door connecting two rooms).

3.3.2 Active badge and active bat

One of the first attempts for a location sensing system was Active Badge[36] which along with most of the early location sensing systems required specialized hardware. Along with the more recent Active Bat system are two of the orst systems in this oeld which are based on distance measurements in order to locate an object. Active Badge uses specialized tags which emit diouse infrared pulses detected by ceiling-mounted sensors. Its accuracy granularity is equal to a room size but it needs one base station in every room. The Badge communicates with the base station every 10 sec. One of its main limitations is the sunlight and ouorescent interference with the infrared pulses.

Active Bat uses an ultrasound time-of-flight(ToF) technique to provide accurate physical positioning. Specifically, users and objects must carry Bat tags. These tags emit an ultrasonic pulse to a grid of ceiling-mounted receivers and a simultaneous bresetb signal over a radio link. Each ceiling sensor measures the time interval from bresetb to ultrasonic pulse arrival and computes its distance from the Bat tag. The Active Bat has location accuracy of nine centimeters in 95% of the measurements. It needs one base station in every 10 square meters. The Bat makes 25 computations in every sec for every room. This high accuracy though comes at the cost of large infrastructure (ceiling sensor grids) and maintenance cost.

3.4 Bluetooth Indoor Positioning System(BIPS)

BIPS[11] is a location sensing system based on Bluetooth technology. The authors aim for simplicity over accuracy because of their claim that in corporate environments an accuracy of 4 meters is acceptable. The system that they propose is based on the discovery phases of the bluetooth protocol. The system is divided in 3 components; the bluetooth access points (masters), the bluetooth enabled mobile devices(slaves) and the server. The authors suggest two different configurations, BIPSi and BIPSp, that differentiate in that in BIPSi system periodically go into inquiry scan mode and in BIPSp the masters go into paging scan mode when a disconnection of a slave is detected. The masters are responsible for scanning mobile devices in their proximity and the slaves are set into listen mode to await inquiry/paging and connection requests. The masters make use of class 2 bluetooth antennas and thus have a proximity of of maximum of 10 meters. Masters report the devices and the status of the connection with the devices in their proximity to the server, so in case of disconnection the server can direct a nearby master to discover the disconnected device to keep track of the users movement.

BIPSp system produces better results than BIPSi in the transfer times of packets between masters and slaves. The difference is due to the fact that in BIPSp the system does not spent its resources into inquiry scan periodically and thus more resources can be spend in data transfer. In addition inquiry scan generates more noise and thus affects the connections of the other bluetooth devices in the proximity. The location estimation is done per access point with no real knowledge of the actual location. That can work satisfactorily for contextual services but fails to give a real solution to the location estimation problem.

3.5 Global positioning system(GPS)

The most common system for location sensing in use today is the Global Positioning System (GPS)[27]. GPS was developed by the U.S. Department of Defence as a satellite system, predominantly designed for navigation but currently gaining prominence as a timing tool especially in the context of cellular communication systems. GPS is based on a constellation of twenty-four satellites(figure**??**, six in each of three orbital planes spaced at 120° apart and three extra to provide fault tolerance as well as their ground stations. GPS receivers use the satellites as reference points to calculate geographical positions, which are accurate to within a few meters.

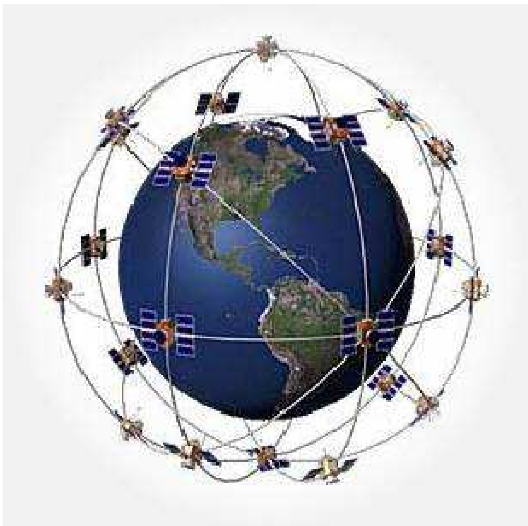

Figure 5: GPS satelite tracking

A GPS receiver uses time measurements relating to the arrival of satellite signals to compute the latitude, longitude and elevation of the location. GPS needs the optical contact with at least 3 satellites. Its precision is better than 10 meters for military use and 100 meters for commercial one(figure6). The last years has been developed the differential GPS (Differential GPS) that improves considerably the precision in 2 with 5 meters. It uses a network of stationary GPS receivers to calculate the difference between their actual known position and the position as calculated by their received GPS signal. The bdifferenceb is broadcasted as a local FM signal, allowing many civilian GPS receivers to bfixb the signal for greatly improved accuracy. Its disadvantages are that it needs the help of a land station and has low degree of renewal.

Figure 6: A commercial GPS device

3.6 Algorithm Fusion

The last years attempts have been made to combine RF technologies[14] and algorithms in order to improve location estimation. Example of this are Selective Fusion Location Estimation(SELFLOC)[18] and Region of Confidence(RoC). The authors of the methods stress that their algorithms are not location estimation algorithms, but methods to merge information from other location estimation techniques and algorithms in order to improve location accuracy. SELFLOC algorithm combines multiple information sources to find the location of stationary users and RoC algorithm tries to solve the problem of aliasing when two locations have similar RF characteristics

In SELFLOC each different source of information is a different branch. During off-line mode(training) of the system each branch is weighted. For the weight calibration in SELFLOC the authors have adopted the Minimum Mean Square Error(MMSE) method. The accuracy of SELFLOC may degrade due to inconsistencies in the characteristics of different regions of the same location. The authors suggest to divide the system into regions and weight each region separately.

RoC attempts to overcome the problem that different the problem caused from classical location algorithms such as triangulation and K-nearest neighbor when 2 or more locations share the same characteristics and thus are being represented similarly in the signal domain. RoC forms a region of confidence where there is a high probability that the true location of the user is there and then performs a further analysis using a location estimation algorithm. Then newly processed region is fed again to RoC for filtering.

The authors tested the algorithms in a typical corporate environment that includes cubicles and small offices. They used 4 Wireless Lan access points and 3 Bluetooth access points and a laptop, featuring both wireless technologies, as a mobile device. The results they present vary but all showed definite improvement over the initial algorithm/method used. The authors tested various algorithms and techniques, independently and in fusion. Results showed that there can be an improvement of of 41%-70% when using multiple technologies along with SELFLOC and 24%-38% when using multiple technologies with RoC.

3.7 Summary

In this chapter we investigated sevaral aproaches on location estimation. The location sensing systems that we presented mostly focused on signal strength based systems (Smart Space, Spreha, Radar, Bluetooth indoor location system) sevaral of them using Bluetooth wireless communication technology[10]. In addition we investigated systems based on distance (Cricket, Active Badge, Active Bat) as well as algorithm and technology fusion methods. (SELFLOC, RoC). Each work is a distinctive aproach on the location estimation problem and all have their advantages as well their disadvantages.

Chapter 4

Cooperative Location-sensing system

In previous chapters we described several approaches on implementing a location sensing system. We presented the challenges, the technologies and techniques involved to implement such a system. In this chapter we present a location sensing system refered as Cooperative Location-sensing system(CLS) [17]. In the following section we describe the algorithms and techniques involved in the location estimation process of CLS and its Bluetooth extension.

4.1 Overview

CLS enables devices to estimate their position in a self-organizing manner, without the need of an extensive infrastructure or training. Estimation process can be aided by possible availability of IEEE802.11 infrastructure as well as of Bluetooth infrastructure. CLS consists of a communication protocol and a voting process. The communication protocol(described in detail in the following section) disseminates positioning information among hosts in the network. A host that seeks its position, uses the position information to compute its position in the voting process. The voting scheme aims to incorporate positioning information from hosts in the network and enables them to estimate their position in a self-organizing and adaptive manner.

All the hosts in the network participate in the communication protocol. There are two types of CLS host:

- **Active host:** The host runs CLS and can compute its own location.
- **Passive host:** The host does not run CLS and cannot compute its own location.

In this thesis we consider an architecture with one active host and several passive hosts. The active host can be either a laptop or Personal Digital Assistant(PDA) and we refer to the passive hosts as Access Points(AP)

CLS runs iteratively at each active host. For each iteration, it considers a snapshot of the network and assumes that all hosts are stationary during that run. An active host reports its position to the other hosts as soon as it computes it during a run. We refer to the duration of an iteration as a CLS run or simply run. The exchange of CLS messages and voting process take place concurrently during a run.

We use a grid-based representation of the terrain. Each host maintains a regularly-spaced grid of cells. Figure 7 illustrates an example of a real terrain and its grid-based representation.

At the beginning of a CLS run, hosts initialize their grid and during the voting process, hosts cast their votes on each individual cell. Each host is configured with a voting weight, a constant, that depends on the confidence of the host about its position estimation. We assume that landmarks have higher voting weight than hosts that compute their position using the CLS, since they know their positions a priori, whereas the latter do not know their position and they try estimate it.

For example, Figure 8 illustrates three hosts, A, B, and C, which contribute with positioning information, the wireless range of host C (RC) and the distance interval

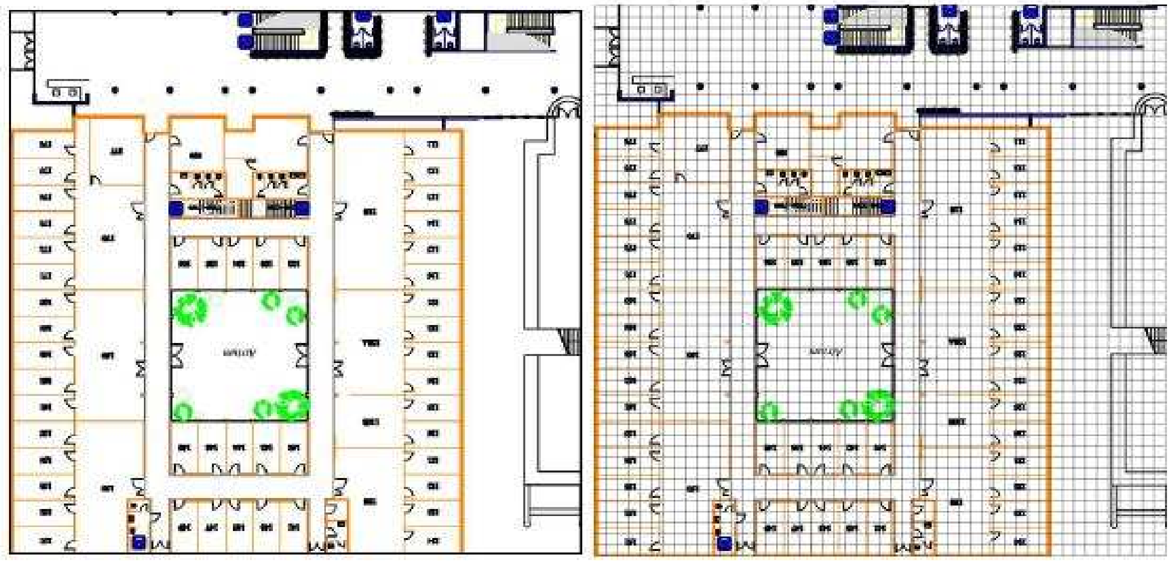

Figure 7: A terain on the left and its grid based representation on the right.

from u, which is the host that wants to estimate its position, to A. In addition it shows the accumulation of votes on the grid of host u after A, B, and C have casted their votes.

4.1.1 Design Goals

The initial CLS implementation was designed in order to fullfil the following goals.

- To be robust enough to tolerate multiple network failures (such as device failures or disconnections) and changes in the environment due to host mobility.
- To be easily extensible to incorporate application-dependent semantics or external (location-related measurements) information.
- To be computationally inexpensive, so that devices with limited capabilities (such as PDAs or sensors) can participate in the network.
- To be suitable for indoor and outdoor environments.

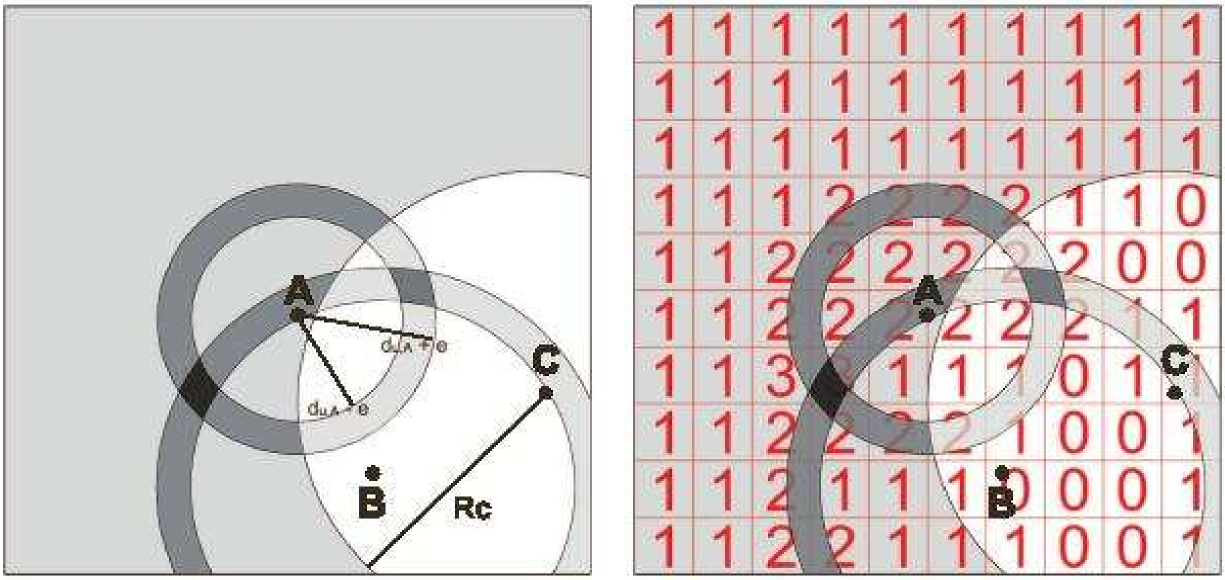

Figure 8: Positioning information of three hosts on the left and accumulation of votes on the right.

- To be scalable, inexpensive, and easily deployable without the need for extensive training and specialized infrastructure.

4.2 Voting algorithm

At the beginning of a run, each peer broadcasts messages to its one-hop neighbors that include its positioning information, namely, its local id, maximum wireless range, and position, if known or computed. We refer to this broadcast update message as positioning message. In the case that the peer is an AP, this message can be in the form of a beacon. A peer records the signal strength values with which it receives these messages and responds by broadcasting its own position estimates.

Each local CLS instance employs an algorithm that transforms (maps) these signal strength values to either distance or positioning estimates. The transformation algorithm can be based on a radio attenuation model or a pattern matching algorithm that relates measurements with position at the terrain or distance estimates between the sender and receiver of that message. Based on the position information of the sender and this distance estimation, the receiver estimates its own position on the local grid. When the local CLS estimates its own position, it broadcasts this set of information, i.e., CLS entry, to its neighbors. Each node maintains a table with all the received CLS entries.

We denote as G_k the grid of the node k and as $v(i, j)$ the probability that the cell $(i, j) \in G_k$ is the position of node k. Each node tries to position itself on its local grid.

To determine its location, each node h gathers position estimations from other peers, and computes its own location using the following algorithm:

1. Initialize the values of the grid G_h with all cells containing zeros.

2. If a signature of the environment is available, compare it with run-time measurements, and for each cell of the grid c, assign a vote of weight $w(c)$ (according to the specified criteria).

3. For each received distance estimation to a peer k with a known or estimated position, perform the following steps:

4. (a) Transform the coordinates of peer k and numbers $d_{k,h} - \epsilon_l$ and $d_{k,h} + \epsilon_u$ to the coordinate system of the grid.

   (b) Determine the region of the grid,$G_{h,k}$, i.e., set of cells for which peer k votes as possible region of node h. The determination can be based on a position-based or distance-based algorithm.

   (c) Increase the value of each cell in $G_{h,k}$ by v_k, where v_k is the voting weight of node k.

5. Assess the values of the cells in the grid and accept or reject the attempt for location sensing.

When a training phase prior to voting is feasible, CLS can build a map or *signature* of the physical space. Such signature is a grid-based structure of the terrain augmented with measurements from peers.

At run-time, the local CLS instance acquires signal-strength measurements from peers, constructs a run-time signature, and compares this run-time signature with the ones that have been generated during the training phase.

4.2.1 Confidence interval-based criteria

During training, a (training) position-level signature based on confidence intervals associates each position of the terrain (cell of the grid) with a vector of confidence intervals. Each entry of the vector corresponds to an AP and the respective confidence interval is the confidence interval based on the RSSI values that were recorded from beacons received from that AP during the training phase. At run time, the local CLS instance acquires a number of beacons from APs, and for each AP, computes a confidence interval that corresponds to the entry for that AP in its run-time signature/vector.

The algorithm assigns a weight $w(c)$ at cell c,

$$w(c) = \sum_{i=1}^{n} \frac{\sqrt{(R_i^- - T_i^-)^2 + (R_i^+ - T_i^+)^2}}{R_i^+ - R_i^-} \tag{1}$$

where n the total number of APs, R_i^+ and R_i^- the upper and lower bound in the run-time confidence interval for the i-th AP, and T_i^+ is the upper and T_i^- the lower bound of the confidence interval of the training phase for the i-th AP.

4.2.2 Example of voting process

We consider hosts A, B and C with known, or estimated position and host u that currently tries to position itself. We discuss this example from the perspective of host u, after it received beacons and updates from A and B and updated its CLS table.

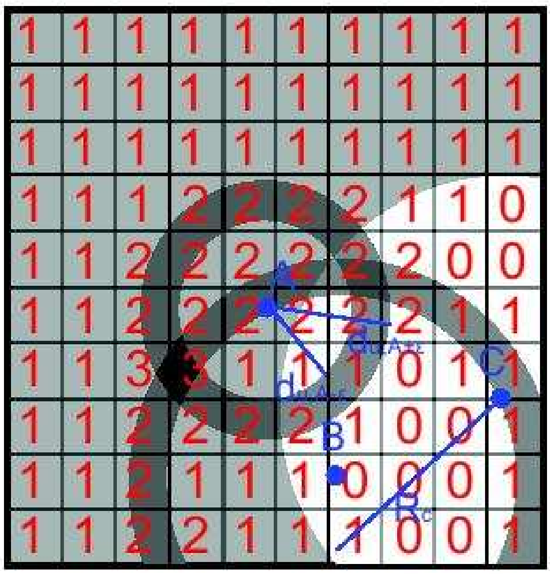

Figure 9: Vote accumulation on the grid of host u after the rest of the hosts have casted their votes.

In figure 9 the grid of host u is shown after it accumulated the votes of hosts A, B and C. On the grid, we have superimposed the positions of A, B and C, the distance estimate between A,the range error e and u ($d_{u,A}$ $-e$, $d_{u,A}$ $+e$), and the transmission range of C (R_C). Each cell is marked with its value, given that A, B and C′s voting weight is one and are the only hosts that have voted so far. The darker an area is, the more voting weight has been accumulated on the corresponding grid cells.

In this example, we assume that host u has not received any beacon or update from C but learns about C from either A or B's update. It then infers that its position is likely to be outside of the range of C and casts a vote for the cells in the grey area outside of the range of C. The set of cells with the maximal value defines a possible solution. In this example, this set consists of the two cells with value ”3”. In order to be accepted, the two conditions of the voting process need to be satisfied. Once a potential solution has been accepted, the algorithm computes the centroid of that set of cells and reports it as the estimated location of the newly solved host. The host does not try to refine further its location estimation during that run, even when it receives additional positioning information from other hosts.

4.2.3 ST and LECT thresholds

Landmarks and nodes that were first to position themselves determine, to some extent, the accuracy of the location estimation of the remaining nodes, since their positioning estimates and errors are propagated in the network through the voting process. To minimize the impact of such errors, CLS imposes the following two conditions:

- The number of votes in each cell of the potential region must be above a threshold. We refer to this threshold as the *solution threshold* (ST).
- The number of cells in the potential region must be below a threshold, denoted as the *local error control threshold* (LECT).

In effect, ST controls how many nodes with known location must *b*agree*b* with the proposed solution. High ST reduces the error propagation throughout the network but delays the positioning estimation. On the other hand, LECT determines the precision of each step. Another metric for oltering the local error can be the diameter of the region that corresponds to the maximum Euclidean of cells with the maximal value in voting weight.

Additional distance estimations from nodes with known location increase the voting weight and narrow down the potential region. The values for ST and LECT depend on network characteristics, such as the density of nodes, and landmarks, and accuracy of the distance estimations. To prevent CLS from failing to report a position, both thresholds can be adaptively relaxed after rejecting potential solu- tions. Once the above conditions are satisoed, CLS reports the centroid of the potential region as the estimated location of the device.

Information related to occupancy and topology of the environment and presence, trajectory, and speed of the user can be also incorporated in CLS to either exclude regions in which a device is very unlikely to be located or enhance their weight as likely locations of the device. The communication protocol depends on the architecture approach that is adopted which can be distributed or centralized.

4.3 Bluetooth CLS

We implemented an extension to CLS that takes advantage of Bluetooth wireless technology. This addition will be refered as *Bluetooth subsystem*. In addition we extended CLS to take advantage of multiple wireless communication mediums and their respective infrastrutures and estimate location based on two different signal maps(one for each medium).

4.3.1 Bluetooth estimation

Bluetooth subsystem is reposnsible for obtaining RSSI information from passive CLS hosts, Access Points(APs), via Bluetooth wireless tehnology. In each run Bluetooth subsystem obtains measurments to construct a signal map, in order to cast votes and estimate the location, according to the Confidence interval-based approach, presented earlier in this chapter.

Bluetooth subsystem uses the CLS-10 algorithm. CLS-10 performs ten consecutive iterations, finds the position that was reported most frequently(in each iteration had the most votes), and reports it as the estimated position of the device.

4.3.2 Joint estimation

The location estimation based on both CLS subsystems (Bluetooth and IEEE802.11) will be refered as *joint estimation*.

The joint estimation approach takes advantage of both Bluetooth and IEEE802.11 infrastructure using Bluetooth APs and IEEE802.11 APs. This implementation shows that CLS can be a versatile system that can take advantage of various wirelless technologies and infrastuctures to produce an estimation.

The voting process of the system took into consideration the cell candidates from two different signal maps (one for Bluetooth and one for IEEE802.11). For both, the CLS 10 algorithm was used. The two CLS subsystems obtain RSSI measurements sequentially.

In every iteration the system first creates the IEEE802.11 signal map by measurments obtained from the IEEE802.11-CLS subsystem. Then the system creates the Bluetooth signal map by measurments obtained from the Bluetooth-CLS subsystem. When the iterations from both subsystems have finished the system estimates the position based on both signal maps as explained in more detail below.

For each cell the weight in votes is calculated. For: n the total number of APs, R_i^- and R_i^- the upper and lower bound in the run-time confidence interval for the i-th AP and, T_i^+ and T_i^- the upper and the lower bound of the confidence interval of the training phase for the i-th AP The weight $w(c)$ at cell c is:

$$w(c) = 1 - \sum_{i=1}^{n} \frac{\sqrt{(R_i^- - T_i^-)^2 + (R_i^+ - T_i^+)^2}}{R_i^+ - R_i^-} \tag{2}$$

After the weights have been calculated for both mediums we find the cells for both the Blueooth map and IEEE802.11 Map with the maximum weight in votes.

For:

W the vector of points with the most votes for the IEEE802.11 map, B the vector of points with the most votes for the Bluetooth map, $w_w(c)$ and $w_b(c)$ the weights(votes) for the for IEEE802.11 and Bluetooth map individual cells respectively

we find the vectors:

$$W = argmax[w_w(c)] \tag{3}$$

$$B = argmax[w_b(c)] \tag{4}$$

After we have obtained the max points from each map we create a third vector P that contains all the points x_{ij} from the individual IEEE802.11 and Bluetooth vectors W and B respectively. Eventually we perform a calculation for each of the axes to find the centroid c_{kl} of the max points P

for n the number of max points:

$$c_k = \sum_{i=1}^{n} \frac{x_i}{n} \tag{5}$$

$$c_l = \sum_{j=1}^{n} \frac{x_j}{n} \tag{6}$$

4.4 Summary

In this chapter we presented CLS, a location sensing system, that enables devices to estimate their location in a self-organisisng manner without extensive training. We desribed the estimation process and the voting algorithm behind the estimation. In addition we presented how CLS can take advatage of existing IEEE802.11 as well as Bluetooth infrastructure to colculate the position. Finally we showed how CLS can take advatage more than one wirelless communication mediums simultaneusly and the algorithm for the estimation fusion of two mediums (IEEE802.11 and Bluetooth).

Chapter 5

Evaluation Experiments

5.1 Experiments setup

To investigate the performance of the proposed system we conducted two sets of experiments. The first set was conducted utilizing only Bluetooth technology. The second set was conducted utilizing both Bluetooth and IEEE802.11 technologies, simultaneously from the same client device, for a joint location estimation. For the evaluation we tested the system under two different environment conditions:

- Baseline case(ideal conditions): Experiments were performed at night with no people, or other moving physical obstacles in the testbed area. This category serves only as reference for comparison with the normal-conditions performance of the system.
- Normal case (normal conditions): Experiments were performed noon with many people and other moving physical obstacles present in the testbed area. This category provides the evaluation for the performance of the system for real indoor use, such as in offices.

Each experiment was conducted in two phases:

- Training phase: In the training phase we obtain signal strength information for different positions in the testbed area to use for comparison during the run-time phase.

- Run-time phase: In the run-time phase we obtain signal strength information and compare it, using CLS algorithms with the signal strength information obtained in training phase, to estimate the location

Both the training and run-time phases of the experiments took place in the Telecommunication and Networks Laboratory (TNL), an area of size 7mx12m. To generate the signal strength signatures for the training, CLS requires thirty(30) Receiver Signal Strength Indicator (RSSI) samples from each cell for each AP. (Figure 10). Training under the same conditions allows us to obtain similar RSSI measurements during the runtime phase and increase the accuracy of the the system. This phase provides with a set of values correlated to specific positions in the testbed area and thus enables us to perform comparison with the equivalent runtime set.

To evaluate the performance of the system, for each experiment, during the run-time phase, we took thirty(30) sample location estimations from cells in the testbed area. The estimated cell was compared to the real cell (the cell that the mobile device running CLS was on) to calculate the location estimation error. In order to evaluate the system we found the median location error in meters for each experiment.

5.1.1 Bluetooth subsystem setup

For the experiments, we deployed three Bluetooth hotspots, placed in the TNL as indicated in figure 10. Each hotspots had a class 2 Bluetooth adapter (∼10 meters proximity) installed. We preferred class 2 adapters over class 1 adapters (∼100 meters proximity) to produce granularity of signal strength across the testbed space. A class 1 adapter with an average proximity of 100 meters lacks granularity of signal strength in confined spaces since it has a maximum power output of 20 dBm, as opposed to class 2 adapters with a maximum power output of 4dBm[1]. We found that using a class 1 adapter results in obtaining similar measurements for 75%

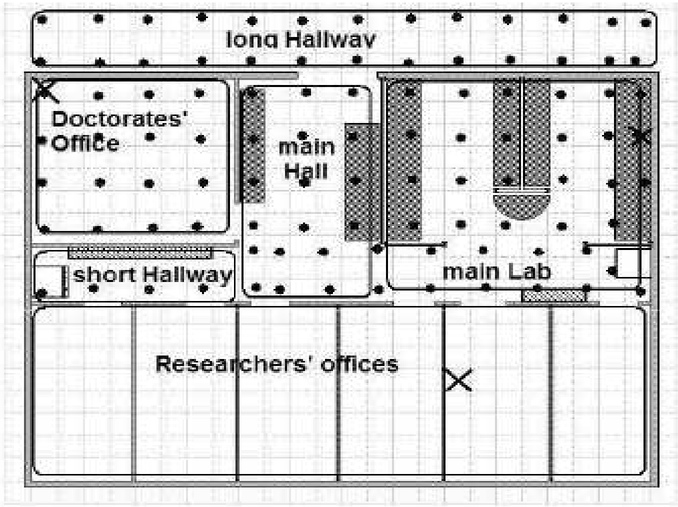

Figure 10: TNL floorplan the black dots indicate the positions where measurements in the training phase were obtained and the cross the posistion of each Bluetooth Hotspot

of the positions in the testbed area and thus renders location estimation based on comparison of the training set and the run-time set highly erroneous. To successfully estimate a location, each position should have distinctive characteristics. In our case this characteristic is Signal Strength and its value is affected by certain location characteristics such as distance and large unmovable obstacles such as walls. A class 2 adapter was installed in the device running the CLS client as well.

CLS Blueooth subsystem utlizes the BlueZ[2] Linux Bluetooth stack to communicate with the Bluetooth adapter on the client device. Bluetooth signal strength information is acquired from Receiver Signal Strength Indicator (RSSI). To Obtain RSSI information a connection between the device has to be established. Thus, the CLS Bluetooth subsystem first establishes a connection with the hotspots, and then proceeds in obtaining the RSSI information from the packets, exchanged with each hotspots individually, carrying RSSI information.

5.1.2 IEEE802.11 subsystem setup

In the testbed area there are 11 APs in total, out of which, 3.5 APs, in average can be bdetectedb and utilized at any given cell. In order to obtain signal strength values from the IEEE802.11 infrastructure we used two different scanners. The first, iwlist from Wireless Tools for Linux[5], polls each channel and obtains the mac address and signal strength measurements (in dBm) from each AP. It has an internal buffer that requires a period of 250ms to fill with values. When the buffer is filled iwlist makes it available to the system. The second, tcpdump, is a passive scanner that relies on libcap for retrieval of each packet. Tcpdump analyzes each packet Intel 802.11 radio tap header and retrieves the mac address and signal strength value, as reported by the hardware, when packet is captured.

5.1.3 Bluetooth-IEEE802.11 interference

Bluetooth devices transmit small packets (500-700 bytes) using frequency hoping spread spectrum (FHSS) with a rate of 1600 hops per second. This high rate provides the advantage of spending little time in a certain frequency that suffers from strong interference. On the other hand IEEE802.11 devices are based on direct sequence spread spectrum (DSSS). Unlike Bluetooth, they transmit in a fixed frequency.

Bluetooth signal occupies 1 MHz of the frequency spectrum (Figure 11) with hoping taking place in 79 frequency centers. Thus, the signal ends up occupying 79 MHz of the frequency spectrum. IEEE802.11 dictates a spreading ratio of 11, thus, occupies 22 MHz of the frequency spectrum. Thus, we can calculate that the probability of a Bluetooth device trying to transmit in a frequency occuppied by IEEE802.11 is 27.8%[34].

Devices following Bluetooth specification 1.2 (or later) use the adaptive frequency hopping technique forcing them to stop using a certain frequency if it is already occupied[1]. This results in an even smaller probability of interference and, unless all

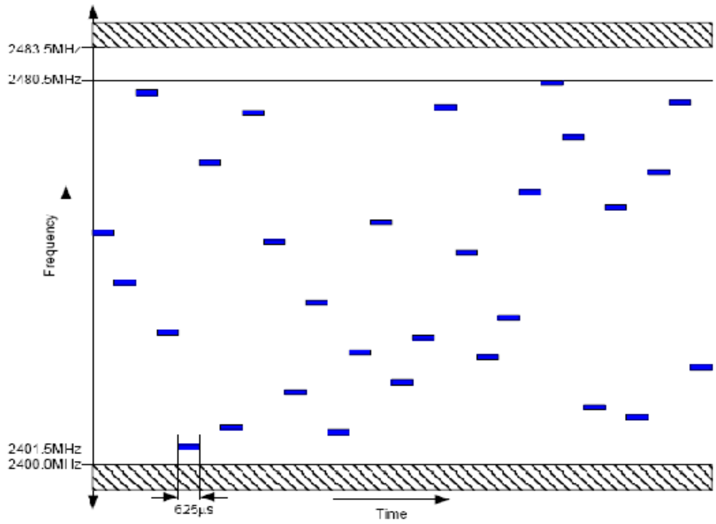

Figure 11: Bluetooth frequency occupancy[34]. Bluetooth occupies 1 MHz of the frequency spectrum at each hop.

the the frequency spectrum is occupied, it posses no problem for the communication using either medium[6]. For the proposed system all our adapters conformed to the Bluetooth specification 1.2.

5.2 Evaluation experiments

As it was mentioned above, we performed the experiments under both ideal conditions (base-line case) and normal conditions(normal case):

- Baseline(ideal) conditions experiment were conducted without people, or other moving physical obstacles in the testbed area. In addition, in the the testbed area there are around twenty five workstations and various other equipment such as printers and laptops, but the majority of the equipment remained inactive throughout the experiment.
- Normal conditions experiments were conducted at noon, which is the peak time (in terms of people presence and bustle) for the Laboratory. At any given

time a minimum of ten people were present in the area and were constantly moving, going about their usual daily activities. In addition, in the testbed area there are around twenty five workstations and various other equipment such as printers and laptops and the majority of the equipment remained active throughout the experiment.

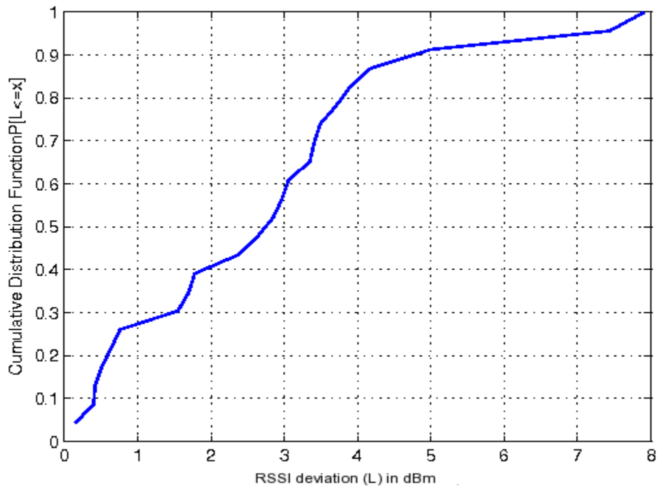

Figure 12: CDF plot showing a median of 2.7 dBm deviation of the RSSI between base and normal conditions measured on the same testbed grid cells.

We performed experiments to determine the impact of the physical obstacles, present under normal conditions, to the system. In these experiements,for each AP, we obtained thirty(30) signal strength measurments from thirty(30) cells in the testbed area under base conditions and then we repeated the measurments from the same cells under normal environment conditions. We found that the RSSI under normal conditions had median of 2.7 dBm (Decibels below 1 milliwatt) deviation from the base conditions (Figure 12).

For an example, please see table 3, above that features the RSSI deviation for cell 12,16. Each value in the table is the mean of the thirty(30) measurement taken from each AP. We can see that measurements obtained under normal conditions have a mean value lower than measurments obtained under ideal conditions. The physical

case / AP	**AP 1**	**AP 2**	**AP 3**
baseline	-2.16 dBm	0.0 dBm	-5.9 dBm
normal	-10.07 dBm	0.02 dBm	-6.8 dBm

Table 3: Signal strength devation example from ideal and normal conditions for cell 12,16

obstacles affect signal strength measurments resulting in lower RSSI measurments. Using class 2 Bluetooth adapters the RSSI ranges from 0 to $\sim$-18 dBm and thus, a median deviation of 2.7 dBm under normal conditions is a 15% deviation from the values obtained under ideal conditions.

5.2.1 Bluetooth only estimation

The fisrt set of experiments comprised of measurments obtained utilizing only Bluetooth wireless connectivity technology. A single mobile device was employed to run the CLS client with a single Bluetooth class 2 adapter installed on it. The expreriments were conducted under both base and normal environment conditions.

The algorithm used for all experiments in this set was CLS-10. In each iteration the Bluetooth-CLS subsystem obtains thirty(30) RSSI measurements from each AP to produce the mean RSSI value that is used in the estimation. The 10 iterations required from the CLS-10 algorithm are performed by the CLS Bluetooth subsystem in less than 1 second resulting in a fast location estimation. We found a median location estimation error of 1.5 meters under base conditions and a median location estimation error of 1.7 meters under normal conditions (Figure 13). We also performed experiments to validate our results. We performed three extra Bluetooth-only estimation experiments under normal conditions with the same method as the previous experiments. The results (Figure 14) indicated a mean location error of 1.66 meters validating our previous results of 1.7 meters. The median location estimation error , was 1.58 meters, 1.6 meters and 1.8 meters for the first, the second and the third validation experiment respectively.

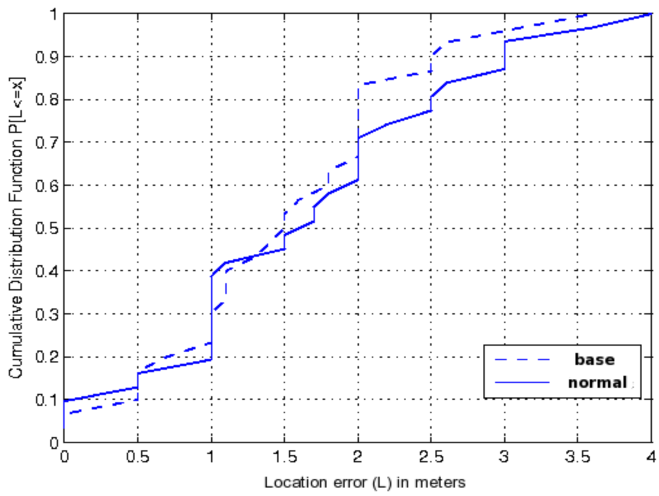

Figure 13: CDF plot showing a median of 1.5 meters error under base conditions and 1.7 meters error under normal conditions in the Bluetooth estimation experiments.

We found a small impact of the environment conditions(ideal / normal) on the performance of the system. The median location error of the system under normal conditions is higher by 0.2 meters. This deviation in performance is caused by the deviation in measurments obtained in the training phase and in runtime phase. The deviation is caused by the effect of moving physical obstacles, on signal strength, in the testbed area, as explained on the previous section.

5.2.2 Joint Bluetooth/IEEE802.11 estimation

The second set of experiments comprised of measurements obtained utilizing both Bluetooth and IEEE802.11 technologies. A single mobile device was employed to run the CLS client equiped with a single Bluetooh class 2 adapter and with a IEEE802.11 card. The CLS client running on the device employed both technologies simultaneously to obtain singal strength values from both mediums in order to estimate the location.

The voting process of the system took into consideration the cell candidates from two different signal maps (one for Bluetooth and one for IEEE802.11). For both,

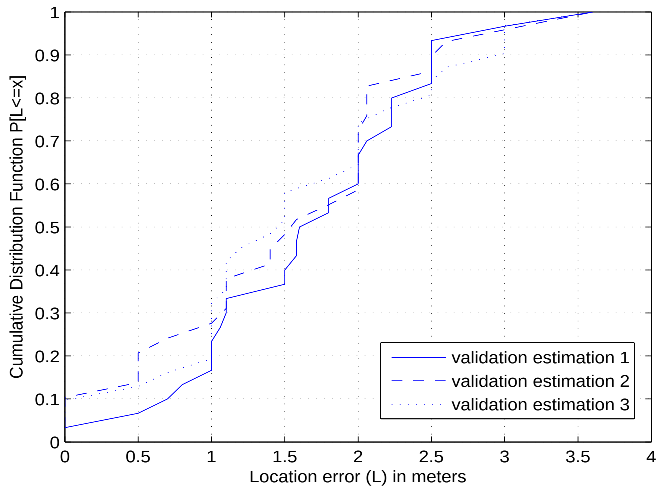

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Figure 14: CDF plot showing a median location error of 1.58 meters, 1.6 meters and 1.8 meters, producing a mean location error of 1.66 m. that validates our previous results in Bluetooth-only estimation experiments.

the CLS 10 algorithm was used. In each iteration each of the two CLS subsystems obtains thirty(30) RSSI measurements from its resptective APs to produce the mean RSSI value that is used in the estimation.

CLS-IEEE802.11 subsystem requires significantly longer time(around one minute), than the CLS Bluetooth-subsystem, to perform the iterations of the CLS-10 algorithm. The delay is caused by the time-consuming operation of filling the iwlist internal buffer as explained in a previous section. The two CLS subsystems obtain RSSI measurements sequentially. The overall time of estimation is not affected by the Bluetooth-CLS subsystem, since Bluetooth estimation requires less than one second. The two CLS subsystems obtain RSSI measurments sequencially. Performing the interations of the two subsystems sequentially minimizes the probability of intereference between packets of the two medium. In every iteration the system first creates the IEEE802.11 signal map by measurments obtained from the IEEE802.11-CLS subsystem. Then the system creates the Bluetooth signal map by measurments obtained from the Bluetooth-CLS subsystem. When the iterations from both subsystems have finished the system estimates the position based on both signal maps as explained in more detail in the previous chapter.

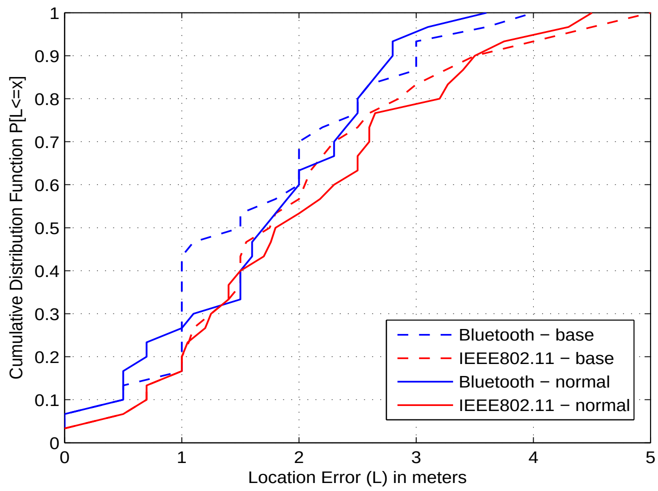

Figure 15: CDF plot showing of location error estimation for each subsystem separately, in both baseline case and normal case.

Running CLS with a joint Bluetooth/IEEE802.11 estimation we found a median location estimation error of 1.3 meters under base conditions and a median location estimation error of 1.6 under normal environemnt conditions (Figure 17). As we saw earlier the Bluethooth only estimation using the CLS-10 algorithm was 1.7 meters under normal conditions. The results we obtained from the joint estimation indicate that the two mediums can work complementary and increase the performance of the system. As in Bluetooth estimation, we found that there is a small impact on the performance of the system due to the presence of many people and other moving physical obstacles.

5.3 Bluetooth estimation vs. joint estimation

The experiments that we performed showed that both the Bluetooth estimation and the joint estimation can perform very well at normal conditions, even though, the presence of many people, or other physical obstacles has as small impact. Both

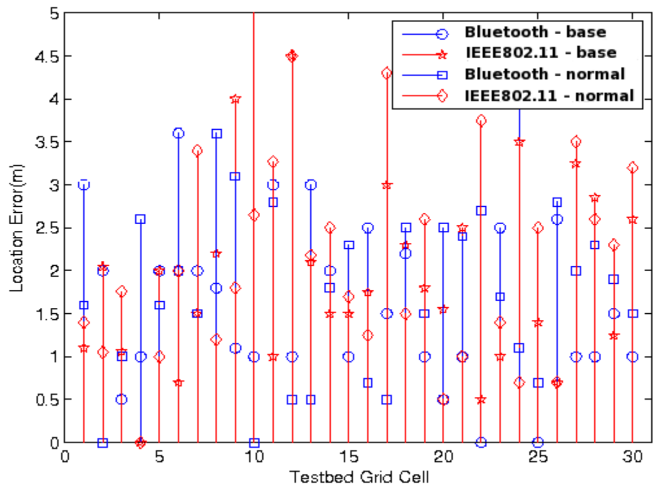

Figure 16: A plot showing the location error of each medium for the same grid cells under base and normal conditions for the joint estimation.

estimation perform better than IEEE802.11-CLS[35] that has an median location of 1.8 meters under normal conditions. The performance of joint estimation however, utilizing both the Bluetooth-CLS subsystem and the IEEE802.11-CLS subsystem, is better than both single medium estimations since, as it was presented in the previous section, the two mediums work complementary.

Joint estimation requires two separate hardware components that need to be installed on the client device, rendering that solution more expensive than single medium estimation. Bluetooth class 2 adapters are cheap (10-20 €) and are suitable for older mobile devices that would be more expensive to upgrade them with a PCMCIA, or USB, IEEE802.11 card. In addition a Bluetooth adapter consumes less power than an IEEE802.11 card rendering this solution more power efficient since the maximum output power of bluetooth (class 2 adapters) is 0.0025 W(4 dBm)[1] and the maximum output power of IEE802.11(in europe) is 0.1 W(20 dBm). Bluetooth estimation requires less than a second for the location estimation in contrast to the IEEE802.11 estimation tha requires approximately one minute. The delay, as it is explained in previous section is due to the delay of iwlist to fill its internal

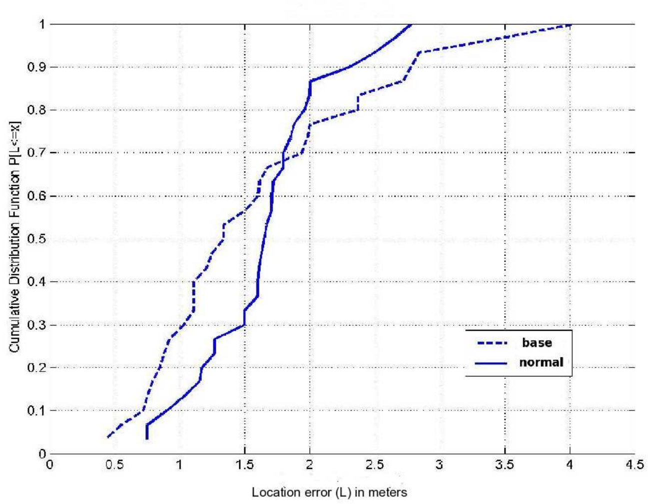

Figure 17: CDF plot showing a median of 1.3 meters error under base conditions and 1.6 meters error under normal conditions with a joint Bluetooth/IEEE802.11 estimation in the joint estimation set of experiments.

buffer. Thus depending on the priority of the requirments each solution has its advantages and its disadvantages. For better performance one should choose the joint estimation. That, though, comes at the price of greater power consumption, more expensive equipment and more time needed for the estimation.

factor / method	**Bluetooth estimation**	**joint estimation**
location error	1.7 m	1.6 m
maximum output power	0.0025 W	0.1 W
estimation time	<1 sec	~1 min
equipment cost	10-20 €	50-60 €

Table 4: Bluetooth estimation and joint estimation comparison

5.4 Summary

In this chapter we presented the performance analysis of Bluetooth-CLS. Initially we focused on several parameters of the evalution experiments such as the different conditions under which we performed the experiments and the hardware that we

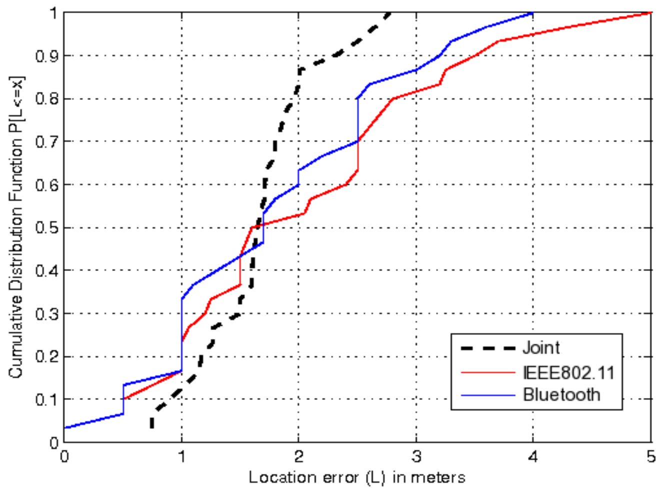

Figure 18: CDF plot showing median location error of 1.7 meters for Bluetooth estimation, 1.8 meters for IEE802.11 estimation and 1.6 meters for joint estimation under normal conditions.

selected. We performed evaluation experiments for both Bluetooth estimation and joint Bluetooth-IEEE802.11 estimation. We investigated the interference between the two wireless communication technologies as well as the impact of psysical obstacles on the signal strength and the performance of the system. Single Bluetooth estimation has a median location error of 1.7 meters, on normal conditions, and joint estimation has a median location error of 1.6 meters, both performing better than single IEEE802.11 estimation. Finally we compared single Bluetooth estimation and joint estimation and presented their main advatages and disadvantages.

Chapter 6

Comparison with related work

There are several aproaches on the location estimation problem. In this section we will compare CLS with other similar work. Mainly we will focus on signal stength based system but we will refer to other aproaches as well.

6.1 RADAR

RADAR[7] uses maps of signal strength similar to the ones we exploit in the previous chapter. The signal strength measurements employed a signal strength map with approximately one scan every square meter. More particularly, RADAR uses only a wireless networking signal, employing nearest neighbor heuristics and other pattern recognition techniques for localization. The authors report a median location error of more than 2 meters for stationery users. CLS has a median location eroor of 1.7 using only Bluetooth estimation and 1.6 using joint estimation. In addition CLS can take advantage of different wireless technology infrastructures to improve its performance.

6.2 Cricket

Cricket[29] is location sensing system that works using quite a different aproch. Cricket uses specialized ultrasound and radio frequency hardware to create the infrastructure and embeds receivers in the object being located. Our work is signio-cantly different from theirs, in that Cricket requires investing in extensive infrastructure of specialized hardware, used only for this purpose. On the other hand, our system can operate with limited, or no infrastructure. Furthermore, the infrastructure of 802.11 APs are already widely used and our system does not require additional localization hardware such as the specialized components required by Cricket. Even though Cricket performce better than our system, CLS is very easy and inexpensive to deploy and maintain, contrary to the deployment of the Cricket sensors.

6.3 Smart space

The system is based on multiple antennas access points[9]. Each antenna is located in a different place on the same location in order to obtain a dioerent measurement of the RSSI. To solve the problem of the difference in analogy of RSSI and signal strength they used attenuators for each antenna and thus they changed the granularity of the signal for each antenna allowing them to obtain dioerent measurements for dioerent distances. The system is not expensive to operate as its does not require special hardware. From the other hand it requires training and extra configuration of the antens to operate. Our system does not require training and does not have the overhead any extra configuration.

6.4 Spreha

The system is build on Place labs' initiative of RF/WiFi reference point-based location system[22] and uses Bluetooth wireless communication technology. The authors stress that flexibility and simplicity is more important than accuracy for inddor posistioning. Their aproach and target is differnt than CLS's aproach and goal. They emphasize on the usage by contextual services. They make use of a novel artifact taxonomy on the components of the system that is rather complicated in contrast to their goals. The estimation is based on tags that each artifact has and what other artifacts each artifact can "see". Spreha requires atagging and categorizing all the components of the system that an be a quite expensive and tidious task. On ther other hand CLS does not require any special equipment or extensive training.

6.5 In-building location using Bluetooth

The system takes a simililar aproach to CLS in the estimation problem. One of the systembs main design goals is its architecture to be independent from the algorithm used for location estimation[16]. The system provides the underlying system components and communication mediums but the researcher is free to use any algorithm he wishes to perform the estimation such as triangulation or scene analysis. A trainig phase is required. During the training phase the system estimates the RSSI value with each of the access points for a known location and the correlation of RSSI value along with the location is stored for future reference. In contrast to CLS the estimation is made in a server and not the client device. This is a privicy concern since the estimation is managed centrally. As in CLS the system can take advantage of several technologies for the estimation. CLS though can use several technologies simultaneously for a joint estimation.

6.6 Active Bat

Active Bat uses an ultrasound time-of-flight(ToF) technique to provide accurate physical positioning. Specifically, users and objects must carry Bat tags. These tags emit an ultrasonic pulse to a grid of ceiling-mounted receivers and a simultaneous reset signal over a radio link. Each ceiling sensor measures the time interval from reset to ultrasonic pulse arrival and computes its distance from the Bat tag. The Active Bat has a much better than CLS performance with accuracy of nine centimeters in 95% of the measurements. That though comes at the cost large infrastructure (ceiling sensor grids), maintenance cost, and specialzed hardware in contrast to CLS that doens't require any specialed hardware or extensive infrastructure.

Chapter 7

Conclusion and future work

In this study we presented CLS system, a location sensing system that allows devices to estimate their postition without extensinve training, in a self-organising matter. In particular we presented an extension to CLS that takes advantage of Bluetooth wireless commmunication tecnology and can be used for Bluetooth estimation, as well as, for joint Bluetooth-IEE802.11 estimation. We investigated the performance of the system and the impact psysical obstacles have on it, as well as, on signal strength. Implementation and performance evaluation of the Bluetooth subsystem shows that CLS is a location sensing system that can take advantage of multiple modalities simultaneusly and increase its performance.

We performed experiments both under normal conditions and under ideal conditions. During the evaluation experiments for Bluetooth estimation we found a median location error of 1.7 meters under normal conditions and 1.5 meters under ideal conditions. During the evaluation experiments for joint estimation we found a median location error of 1.6 meters under normal conditions and 1.3 meters under ideal conditions. Due to an iwlist internal buffer the IEEE802.11 subsystem causes the joint estimation to take significantly longer ($\sim$1 minute) than the Bluetooth evaluations ($<$ 1 second) Thus, one, depending on his/her priorities (accuracy vs. estimation time), should select the preffered method.

During our experiments we found a small impact of psysical obstacles, stationary or mobile, on the performance of the system. Under ideal conditions, with no psysical obstacles present in the testbed area, the system has a lower, by 0.2 meters, median location error than under normal conditions for the Bluetooth estimation. In addition, under ideal condition the system has a lower, by 0.3 meters, median location error than under normal conditions for the jointh estimation. We found that the signal strength measurments obtained under normal conditions have a 15% deviation from the signal strength values obtained under ideal conditions.

We plan to extend CLS to support multiple voting algorithms for the supported wireless technologies. This way each modality would be able to produce an estimation based on a different voting algorithm. In addition, in the case of multiple modalities we could alter the joint estimation algorithm to include parameters such as the weight of individual modalities. This would make CLS more adaptable to certain conditions that a particular CLS module produces better, or worse, results than another CLS module. The weight individual modlaities will alter dynamically based on the conditions that would be detected from the RSSI measurments. In addition, both modalities could cast their votes in the same signal map in order for moddalities with more weight to have a stronger influence on the estimation process. Finally, we will evaluate the performance of the system using more Hotspots in the testbed area and experimenting with the topology of these hotspots.

Appendix A: Sample Bluetooth-only estimations

Real position	**Estimated Position**
5,11	7,15
7,11	11,12
5,13	8,15
6,12	11,11
9,12	11,12
8,12	11,12
11,10	11,15
9,10	12,9
12,9	11,12
11,14	10,13
12,16	10,20
10,19	8,16
8,19	8,16
7,14	8,15.4
10,15	11,12
8,12	6,11
5,21	10,21
12,20	8,20
8,19	12,18
9,15	11,14
8,14	10,10
6,10	10,9
4,21	6,21
6,21	6,21
8,21	6,21
12,13	12,14
10,16	6,16
6,16	11,16
10,11	14.5,11
6,11	6,14

Table 5: Validation estimation 1

Real position	Estimated Position
6,21	12,21
8,21	12,21
10,17	11,16
4,18	6,16
8,16	12,16
5,11	12,9
6,12	6,16
10,13	12,16
10,10	12,11
12,11	10,11
6,16	12,16
6,16	8,16
6,21	12,21
8,20	12,20
12,16	10,16
11,10	6,11
9,9	12,9
8,12	6,16
10,21	12,21
5,16	6,16
8,16	6,16
10,16	10,16
11,16	10,21
9,11	12,11
6,11	6,11
8,11	10,16
8,11	6,11
8,12	6,11
13,12	12,14
12,18	12,21
6,21	12,21
6,16	6,16
8,16	6,16
8,12	6,11

Table 6: Validation estimation 2

Appendix B: Sample signal map

The map is read in pairs by the system in comma separated values. The first pair is the coordinates of the cell. Each of the following pairs represents RSSI information for each AP. The first value is standard deviation of the RSSI values and second is the mean RSSI value. Below we present 6 cells of the map.

$10, 10 - 0.646539, -1.547010 - 6.281320, -7.185347 - 8.082135, -8.651198$

$10, 16 - 6.890169, -7.7549930.000000, 0.000000 - 6.690152, -7.843182$

$10, 19 - 5.004845, -5.5758000.000000, 0.000000 - 6.003102, -6.730232$

$10, 20 - 5.480465, -6.325987 - 0.242782, -0.757218 - 7.408382, -8.591618$

$10, 9 - 1.316042, -1.974280 - 8.322135, -9.411198 - 5.705115, -6.761551$

$11, 11 - 0.139345, -0.634849 - 7.183612, -8.149721 - 8.526398, -9.273601$

Appendix C: Sample training values

In order to train the system, training RSSI samples for the grid cells must be obtained. Each trainig sample has 30 RSSI measurments for each of the APs (12 measurments for each AP are presented here). Each line represent values for on AP. At the start the mac address of the AP is present and follow the RSSI values. Training values for all the grid cells are then transformed to the Signal Map presented in Appendix B

$00:11:67:58:bf:ca\ -7-7-6-7-9-7-6-4-5-6-6-6$

$00:11:67:58:c7:f1\ -5-1-1-2-10-4-2-4-3-2-1$

$00:11:67:5c:47:58\ -5-6-5-4-3-4-3-3-2-4-4-2$

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