Dynamic Object Binding for Opportunistic Localisation

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***Abstract*—In this paper, dynamic object binding is proposed to improve the opportunistic localisation system. Object binding will be realised using Bluetooth. Many different techniques are already fused in the opportunistic localisation system, since Bluetooth is integrated in almost all mobile devices, this sensor will be incorporated in the opportunistic localisation fusion algorithm. In order to correctly use Bluetooth for object binding, some important features like operating range, influence of obstacles and scan time are analysed. A new measurement model is added to the particle filter engine to process incoming Bluetooth data. The client devices are continually scanning for other adjacent Bluetooth devices, this information is sent to the server where the client device position is estimated, based on the other adjacent Bluetooth devices, which are located through other means. This way object binding is realised.**

***Index Terms*—object binding; opportunistic localisation; Bluetooth**

I. Introduction

Today, localisation techniques are widely spread and already integrated in many applications such as GPS car systems, Google Earth, etc. Outdoor localisation is mostly accomplished by means of GPS, but usually GPS does not work indoor because there has to be a minimum of four satellites in line of sight, which is usually not the case indoor. There we can use WiFi [1] or GSM [2] or even other techniques such as Bluetooth [3], Zigbee [4], Ultra Wide Band (UWB) [5].

One big challenge is fusing these techniques into a single system. Acquire the sensor data of multiple sensors can be realised because most mobile devices such as Personal Digital Assistants (PDAs) and smart phones are very often equipped with GSM, GPS, WiFi or a combination of these. A system which combines this technologies is called Opportunistic Seamless Localisation System (OLS) [1].

This solution combines the above mentioned technologies together with the information of accelerometers, compass and camera . All these approaches are seamlessly fused by using an adaptive observation model for the particle filter, taking the availability of every technique into account. A particle filter [6] is a sequential Monte Carlo based technique used for position estimation. Since we are working with a real-time system, it is even harder to estimate the correct position therefore heavy and numerous calculations are not recommended. Limiting the number of particle filters is recommended in order to avoid numerous time-consuming calculations. For example, when this system is implemented at an airport where many devices are present, the system might be delayed due to these calculations for all those devices. Obviously, some devices will travel together such as people by bus, so that it is not necessary to calculate all their positions with different particle filters. Instead, we could combine all these objects and bind them in one group, in which case we only have to calculate one position for this group. This is one of the reasons why Bluetooth may be useful.

Bluetooth is a useful technique to detect other adjacent Bluetooth devices. Which would enable the possibility to detect whether people are moving together. Another interesting reason to use Bluetooth may be the possibility to locate unknown people. This could be useful to determine the amount of people in every area.

This paper is structured as follows: at first the scanning method is analysed followed by some real experiments to determine the operational range of Bluetooth devices. Thereafter, Bluetooth signal strength values are discussed. This is then followed by a short introduction about opportunistic seamless localisation and the explanation of the Bluetooth measurement model. Finally, the results are showed and the last section gives the conclusion of this paper.

II. Methods

In this section the use of Bluetooth and the localisation algorithm will be explained.

A. Bluetooth

Bluetooth [7] is a technique developed by Ericsson. This universal radio interface in the 2.45 GHz band makes it possible to connect portable wireless devices with each other. Bluetooth uses frequency hopping to avoid interference with other devices, which also use the license-free 2.45 GHz band.

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1) Discovering: There are two ways of discovering [8] devices when using Bluetooth. The first and mostly used method is inquiry-based tracking. In case of inquiry-based tracking, the base station needs to scan for devices and to page all present devices in order to find them. All devices need to be detectable but they need not to be identified in advance. Scanning for devices absorbs a relatively large amount of time because primarily every base station sends a search-packet on all 32 radio channels. Every detectable device that receives this packet will answer. To avoid collision, every device will send his packet with a random delay. This is the reason why an inquiry has to run for at least 10.24 s to be reliable. Many devices are undiscoverable in order to increase the security and privacy of the owner. This is another technical problem that could occur and consequently it is not possible to find these devices by scanning the area.

A second method of tracking is the connection-based tracking. With connection-based tracking, devices are considered to be in a close range when one device has the possibility to connect with another device. All devices have to be paired with each other and this is a major problem when using the Radio Frequency Communications (RFCOMM) layer [9] connections with connection-based tracking. Practically, this requires human input which is time-consuming. Although, some communication services do not require this, it is still necessary that one of both devices knows the other one exists.

In practice, the creation of an Asynchronous Connectionless Link (ACL) [9] and a basic Logical Link Control and Adaptation Protocol (L2CAP) layer [9] connection is universal and authorisation-free. These connections are limited but they are in compliance with the requirements for tracking usage. It is only necessary to know whether a connection is possible and if this is the case, these 2 devices are in the same range. This connection also supports some low-level tasks such as RSSI measurements and L2CAP echo requests.

Both tracking techniques have their own advantages and disadvantages and they are both not ideal. Choosing the correct technique will depend on the situation. When using inquiry-based tracking, it is possible to find every detectable device without the need of knowing the devices in advance. The major disadvantage will be the relatively long scan time. When we choose the other option, connection-based tracking, the time to find the devices will be shorter and there is also the possibility to find undiscoverable devices. The major disadvantage here is the requirement that at least one party knows about the existence of the other one.

Another option could be a combination of both techniques. Combining these two techniques will not decrease the relatively long scan time because we always need to take the longest scan time in account. The advantage of combining both techniques is the possibility to find known 'undiscoverable' devices as well as unknown discoverable devices.

For this project, the first option is chosen because inquiry-based tracking has the possibility to track unknown devices, which will be useful for this project.

2) Range: Bluetooth devices can be divided in three different classes. Generally, class 1 and class 2 are used instead of class 3, which is due to the very short operating range of class 3.

Class	Maximum Power	Operating Range
1	100 mW (20 dBm)	Up to 100 m
2	2.5 mW (4 dBm)	Up to 10 m
3	1 mW (0 dBm)	Up to 1 m

These operating ranges are frequently used to estimate a position since signal strength is not always a good parameter due to effects like reflection, multi-path propagation, ... [10]

The operating range of a Bluetooth device can be defined by the maximum allowable path loss which can be calculated with Equation 1:

$$L_{total} = 20 * \log_{10}(f) + N * \log_{10}(d) + L_f(n) - 28 \quad (1)$$

$$L_{total} = 40 + 20 * \log_{10}(d) \quad (2)$$

where N is the *Distance Power Loss Coefficient*, f is the Frequency (Mhz), d is the distance (meters) between the nodes , L_f is the *Floor Penetration Loss Factor* (dB) and n is the number of floors penetrated.

When working in an open-air environment, Equation 2 which is the simplified version of Equation 1, can be used [11].

As operating ranges will be used to estimate a position, some tests were done in order to decide which maximum range will be utilized. A Dell XPS M1530 laptop has been set up as a base station. The two test devices were a Samsung E250 mobile phone (test device 1) and a Samsung F450 mobile phone (test device 2). All devices, including the base station are devices of class 2. Measurements were started at a distance of one meter away from the base station and afterwards extended by steps of one meter. Every measurement was repeated five times in order to have reliable results.

Fig. 1. Experiment 1

The first experiment, see Figure 1, was done in open space in which the two test devices are in line-of-sight of the base station.

Both test devices could easily bridge a distance of 9 m. Once the distance was increased, test device 1 was not longer detectable. Test device 2 was detectable until we reached a distance of 12 m.

In the next experiment, the influence of obstacles between the

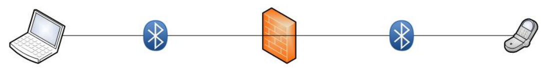

Fig. 2. Experiment 2

base station and the test devices was tested. This test was firstly done with a window between the base station and the test devices. Secondly this test was repeated with a 14 cm thick brick wall instead of a window, see Figure 2.

Theoretically, obstacles comparable to a wall should significantly decrease the Bluetooth signal or even make it impossible to connect with devices behind such obstacles. It is very hard to predict the attenuation caused by an obstacle because every Radio Frequency (RF) signal has multiple ways to reach the other device. Our test with a window started showing problems with detecting test device 1 at a distance of 4 m. Test device 2 remained detectable up to 7 m and at larger distances it started to show some discontinuities.

The following test with a wall instead of a windowpane showed these results: at a distance of 4 m, test device 1 started to disappear and at larger distances, test device 1 was rarely detected. Test device 2 on the other hand, was much longer visible. In a range up to 7 m, test device 2 was still detectable.

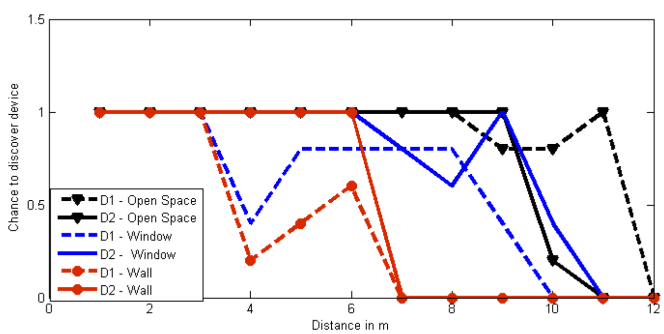

Fig. 3. Results

These results, see Figure 3, showed a general range of 10 m when the base station and test device reside in the same area hence we are working in an open space. Obstacles like walls obviously have some influence on this range. Generally we can decrease the range down to 5 m.

Consequently, when a Bluetooth device detects another Bluetooth device, this estimation will be located in a circular area with a radius up to 10 m in open space. Walls will limit the radius up to 5 m.

3) Signal Strength: RSSI values are often used in order to estimate the proper distance between 2 devices because Bluetooth does not offer an interface to extract the real received signal strength directly [12]. Theoretically, RSSI values should vary exponentially with the real distance but in practice this is not always the case [13].

Although there is no deterministic relationship between distance and RSSI, due to fading, reflection etc. ,there is a correlation: when the RSSI value decreases, we know the distance becomes longer and conversely; when the RSSI value increases, the distance diminishes. This information can be used to discover whether devices move away from each other, towards each other or together.

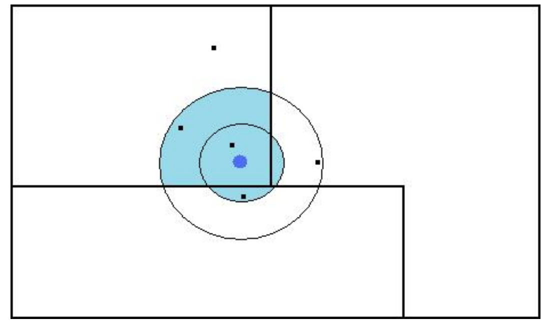

Fig. 4. Range

[14] shows that using RSSI values for calculating the distance between 2 devices is not reliable. Nevertheless, RSSI values could be useful to implement object binding. Object binding should only be realised when 2 or more objects are very close. At this point, the RSSI values will be higher. Nonetheless, these values will fluctuate. In this way, it is necessary to use a range of RSSI values in order to decide whether objects should be bound or not.

In this thesis, RSSI values are not used because they bring up another disadvantage: a device needs to set up a connection with the other device and this will increase the scanning time. Considering the fact that we are working with a real-time system, the scanning time should be as short as possible.

B. *Opportunistic Seamless Localisation (OSL)*

The opportunistic seamless localisation system combines all location related information readily available from multiple technologies such as WiFi, GSM, GPS, accelerometers [15] etc. In this paper we propose a novel method, which allows taking into account also mobile device connectivity via Bluetooth link to other devices as an additional source of location related information which may be successfully utilized by the OSL system for further improvement on location estimation reliability and accuracy. As authors presented in [3] the Bluetooth link connectivity on its own does not provide sufficiently accurate location information for most of the mobile applications. Therefore, to successfully fuse the Bluetooth connectivity information for localising Bluetooth enabled devices, a specific method described in this chapter had to be developed for efficient incorporation into the OSL system fusion location data engine. The OSL fusion engine is based on the recursive Bayesian estimation implemented as a particles filter, therefore, also a likelihood observation function used for the particles weighting was developed.

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1) Communication: Firstly, the client scans for all nearby devices. The MAC address of every found Bluetooth device is sent to the server. In the mean time, the client keeps scanning for devices and will regularly send an update.

At the server side, every incoming MAC address will be compared to a list of known MAC addresses. In this list all primarily known Bluetooth devices are saved. Every Bluetooth device has 4 arguments, at first the MAC address, secondly a boolean to indicate whether the device is fixed or mobile, thirdly the coordinates when the device has a fixed place and at last every mobile device has an ID.

When a match between incoming MAC address and a MAC address in the list is found, these MAC addresses are saved in a list.

2) Measurement Model: The Bluetooth measurement model is designed to deal with different situations. A complete overview of this measurement model can be found in Figure 5.

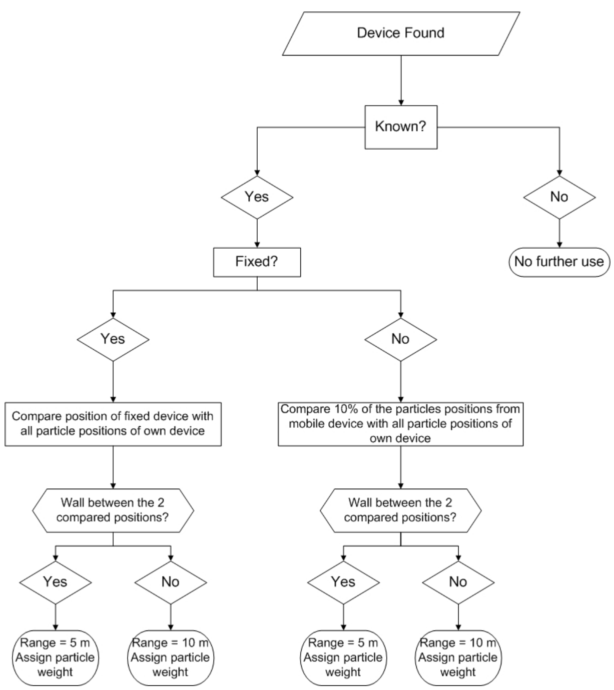


Fig. 5. Flowchart

There are 3 possible options when one or more Bluetooth devices are found. The first option happens when the found devices are unknown. These devices can not be used to localise the client device. Though, these devices can give some interesting information, such as how many devices were present at a certain time in a certain place. This is already implemented at some places such as Brussels Airport [16]. Every Bluetooth device that is discoverable will be detected by fixed antennas. In this way it is possible to measure the time necessary to move from one point to another and consequently it will be possible to calculate the waiting time to pass for example through the safety zone. When the found device is known, there are 2 options left: this device can be a fixed device, this is the second option, or a mobile device which is the third option.

Dealing with the second option, returns a fixed place with the exact coordinates of the fixed device. With the knowledge that a Bluetooth device is only visible within a certain area around that device, the weight of all particles from the client can be adapted.

Calculating the euclidean distance between every particle and the fixed device is the first step. After having calculated the distance between one particle and the fixed device, there will be a wall check. A wall has a big influence on the signal strength and for that reason it is important to know whether there is a wall between the fixed device and the particle. The choice to work with a larger or smaller range depends on the absence or presence of a wall. Based on this range, the new particle weight will be calculated.

If the third option occurs, a known mobile device is found. This device does not show exact coordinates since the location of every mobile device is predicted with a particle cloud. Depending on the situation, a particle cloud can consist out of 100 particles up to 1000 particles. Comparing every particle of the found device with every particle of the client device would be too heavy for a real-time system. For this reason, 10 percent of random particles from the found device are compared to all particles of the client device. Choosing 10 percent still gives us a reliable amount of particles. The coordinates of these particles are loaded and the distance between these particles and the client device particles is calculated. Again, we need to check if there is no wall between the particles. Based on this information, the particle weight can be calculated.

Obviously, it is possible that more than one device is found. For all those devices, previously mentioned options will be looked at and for every device, the correct option will be chosen. Working with multiple found devices, all calculated particle weights are multiplied for every client particle. In this way all found devices are brought into the calculation and the result becomes more accurate.

3) Particle Weight: According to the test results in the section 'Range', a range of 10 m will be used in open space and there will be a range of 5 m when there is an intersection of a wall. It would be inaccurate to assume that discovered devices are always in a range of 10 m with equal chances to be everywhere in that circle. For this reason, using the sigmoid function gives a more realistic image. In this case, the following functions have been used:

$$y = \frac{1}{1 + e^{x-10}} \tag{3}$$

$$y = \frac{1}{1 + e^{x-5}} \tag{4}$$

Equation (3) is used for open space. This function gradually decreases and the particle weight will be based on this function, see Figure 6. Equation (4) is used when a wall between the 2 devices is detected. This function will decrease earlier because the obstacle has a big influence on the signal strength which consequently will decrease quickly.

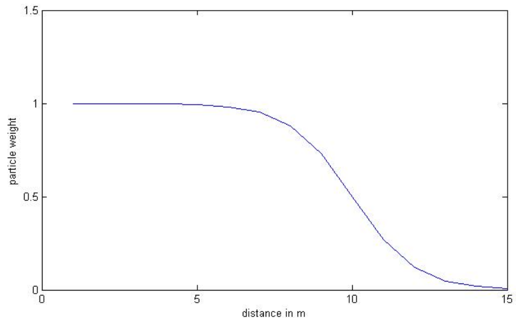


Fig. 6. Sigmoid function

This sigmoid function is S-shaped and by using this function, the use of more complex functions is avoided. Still this function gives a realistic view, due to the smooth curve.

4) Privacy issues: Localising people, often comes with privacy issues and consequently, privacy is a very important subject. Adding the Bluetooth technique does not come with any privacy issues. When scanning for Bluetooth devices, only the unique ID of the device is sent to the server. It is not possible to discover the identity of the owner of the Bluetooth device. There is no connection between the unique Bluetooth ID and the identity of the owner. A connection between those 2 can only arise when this connection is in the system made manually with authorisation of the owner.

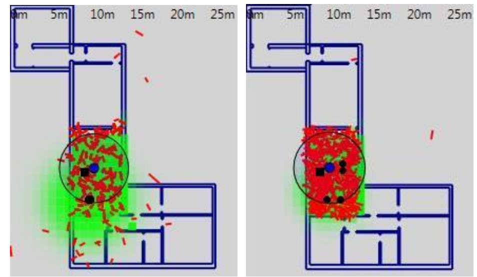
Moreover, every person with a Bluetooth device has the opportunity to shut down his/her device and thus not sending any Bluetooth signals. Most of the time, devices do not need to be shut down. In order to stop sending Bluetooth signals, it is also possible to turn off Bluetooth.

III. RESULTS

For these experiments, indoor localisation is accomplished by using WiFi and Bluetooth. In these tests, the client is only located by using Bluetooth. Multiple tests with fixed and mobile Bluetooth devices were done. The first test was done with one fixed and known device, see Figure 7(a).

The estimated position is located at the center of the circle, the real position is represented by a square and the position of the found and known Bluetooth devices is represented by dots. It shows good room level accuracy, although still some particles -representing different hypothesises- are in adjacent room

Repeating this test, but now with 4 known and fixed devices gives us a better result, see Figure 7(b). You see that all hypothesises, represented by the particles, are now inside the correct room. Using more found and known devices results logically in a more accurate estimation. This is due to trilateration. The location of every fixed device will also have an influence on the accuracy, as shown in Figure 8(c) and 8(d). 8(c) shows a good location of fixed devices, the area where the client can be located is very small and consequently more accurate. In 8(d), all fixed devices are close to each other and therefore, the area where the client can be located is still large.



(a) Test with 1 fixed device (b) Test with 4 fixed devices

Fig. 7. Comparison between test with 1 or 4 fixed devices

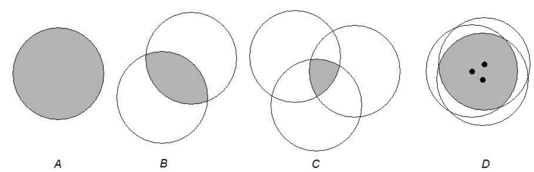


Fig. 8. Trilateration

Obviously the area where the client can be located is a lot smaller when more devices are found. This illustrates why the error rate decreases when the amount of found and known devices increases. Because we are using fixed devices only, it is possible to compare the clients particles with one exact position. Every fixed device has a known position which does normally not change. Therefore the estimated position can be easily calculated with a 100 percent certainty of the location of the fixed Bluetooth device.

Of course this is a kind of localisation which is previously already developed in other research such as [3]. But Bluetooth can be used stronger as a sensor when combined with other technologies to perform object binding.

In dynamic object binding, instead of static devices, other mobile devices will be used as references. Mobile devices do not have one exact and correct position. The likelihood of their position is estimated with a particle cloud. In order to calculate the position of the client, all particles will be compared with 10 percent of the particles from a found and known Bluetooth device. It is possible to increase the threshold of 10 percent, but using more particles will result in heavy calculations, using less particles will make the final result inaccurate.

In this test, the client location, shown in 9(a), is calculated based on the particles of another mobile device, shown in 9(b). Due to the fact that we do not have an exact position of the mobile device, we have to estimate the client position based on another estimation. Consequently, the error rate is increased,

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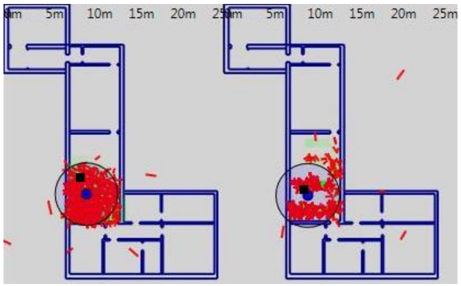

Fig. 9. Test with 1 mobile device

compared to the test with fixed devices. The error depends largely on the correctness and distribution of the likelihood of the dynamic reference device.

Dynamic object binding makes it possible to locate any found Bluetooth device without the necessity to have any other technology embedded in the device itself. Localisation information from all found devices will be used to correctly locate the client device. Merging different technologies improves the final result but within this structure, the position estimation of each device has always been created independent from other devices.

Of course we can combine dynamic reference devices and fixed devices when they are both discovered by the device. This increases the reliability of the estimation.

IV. Conclusion and Future work

In this paper, a method to realise dynamic object binding is presented. We choose Bluetooth to accomplish object binding because of its appearance in many mobile devices. For this project, the Bluetooth technology is fused with multiple other technologies in order to get an accurate localisation system. Some real experiments were done to test the Bluetooth measurement model. These results showed room accuracy when only Bluetooth was used. Obstacles like walls have a big influence on the signal strength which will make it easier to achieve room-level accuracy. This information is incorporated in the Bluetooth measurement model.

Dynamic object biding is used to locate devices which cannot be located by any other technology but can discover other devices which are located by other means. Dynamic object binding can increase the likelihood of the position of these devices.

Further research about acquiring reliable signal strength values can improve the object binding algorithm, since the error rate could be decreased by decreasing the operating range. Object biding can also be used to detect people traveling together to limit the calculations to only 1 object instead of estimating the likelihood of two distinct objects.

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