Indoor positioning using mobile sensors

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1. Introduction and theory

People spend 80-90% of their lives in indoor locations [1], such as shopping malls, libraries, airports, etc. The wide availability of sensor-rich mobiles has boosted the interest and possibility for a variety of indoor location-based services.

Many of these pre-existing solutions, however, rely on WLAN entries, which can hinder their accuracy, due to various environmental factors, such as the exchange and maintenance of WiFi routers position, occlusion generated by walls and even people themselves. This is due to the fact that 2.4GHz, which is the main frequency band for WiFi, is also the resonance frequency of water and human bodies, which contain over 50% water simply absorb the radiosignal, leading to poorer results and anomalies of detection based not on location but simply on the users heading. Also, many aspects, such as diffraction, scattering of the signal, absorption, etc. have to be taken into account when trying to build a location based system on top of WLAAN infrastructure. [2] [3]

This article will try to give a small overview of indoor positioning methods currently used and propose a solution based on research conducted within the fall semester of 2015/16.

2. Related works

2.1 Microsoft Research

The Microsoft Research team's indoor localization takes into account the fact that, while many existing approaches require previously setup infrastructure to achieve any sort of reliable accuracy, it may so happen, that this infrastructure is simply not present or does not offer good enough quality coverage to yield any meaningful location estimates. Essentially, their solution relies on accelerometer based step detection and step length estimation, along with magnetometer measurements for direction. The data from the various sensor is fused with the help of a particle filter, in order to provide a better estimate by bounding the location estimates to more plausible locations on the map. This allows to then provide reasonably good estimate of the user's location, within the confines of the known indoor map. The conceptual model can be seen on figure 1. [1]

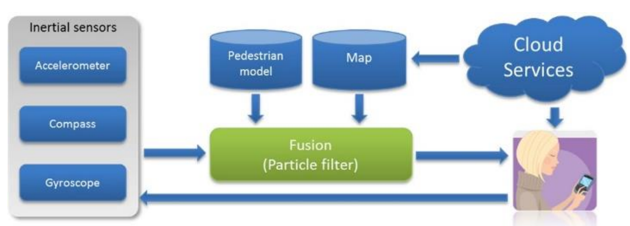

Figure 1: Microsoft Research Localization platform

2.2 Indoor Positioning with Mobile Phones and Visible Light

In addition to the mainstream solutions based on accelerometers and WiFi signals, some researchers have also proposed alternative solutions. This solution works on the principle of beacons, more precisely – visible light beacons. The beacons transmit their identities of coordinates using visible light and switching the light sources on and off at a fast rate in a manner that is unperceivable to humans, but can be detected by the camera of a smartphone. A phone then receives these transmissions using its camera and then tries to pinpoint the location and orientation relative to the beacons coordinate system. According to the source it has a roughly 10-20cm error rate, but this is measured directly below the beacons and when moving outside the area, the detection rapidly drops when moving outside the LED landmarks/beacons. The model of the system can be seen in figure 2. [5]

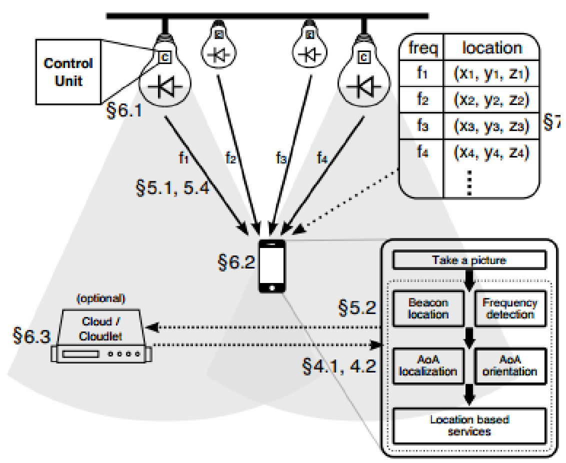

Figure 2: Architecture of the system [5]

2.3 Indoor Positioning Using WLAN Fingerprinting with Post-Processing Scheme

This approach uses WiFi as the primary location estimation provider. It adds to the research by providing a post processing layer by removing floating or missing APs, to filter and adjust the RSS thresholds and using a moving median filter, to compensate for the momentary fluctuations of WiFi signal strength values (RSSI). In the end, this provides fairly accurate location estimates, with an error rate of about 1-5m. [2]

The main problem with this approach is that it uses grid mapping, meaning it defines a grid step and then maps every step to a set of RSSI values for distinct access points. This is a very costly procedure, as the author also specifies himself. [2] For example trying to map any sort of larger buildings would take hours if not days to completely map out and is simply not feasible.

3. Indoor positioning using mobile phone sensors

This section of the work will attempt to highlight the research conducted by the author in the field of mobile indoor positioning. The experiments were mainly conducted in Liivi 2 Mathematics and Informatics building 3rd and 4th floor. The locations were chosen due to the ease of access and pre-existence of the indoor maps for the specific building in the form of GeoRSS which could be then easily translated into GeoJSON format for the reduced bandwidth of resource constrained mobile devices for the actual representation of maps on the mobile device.

The measurements were done using self-written software and software written by Thorben Werner (private repo, no link) based on the Android OS.

The approximate measurement frequency was 50Hz for the linear acceleration sensor and 200Hz for the rotation vector and 30Hz for the pressure sensor, all of which therefore generates a lot of data.

3.1 Measurements and tests

3.1.1 WLAN data measurement and assessment

The goal of this measurement was to gather data about how the WLAN signals could be correlated to a specific user indoor position, how the signals fluctuate due to various conditions etc. Overall, a total of six WLAN signal strength measurements were taken in four locations with three different devices.

The location for the measurements were located on the 4th floor of the Liivi 2 building in or near the common area (rm. 407). The graphical representation can be seen in Figure 1. In locations P1 and P2, the measurements were conducted in two parts – one with the devices directly on the floor and one with the devices on a table, approximately 1m from the floor.

Figure 3: Locations of the measurements taken

The devices used were LG H440n (LG Spirit), OnePlus One A001 and LG Nexus 5. The devices conducted the measurements in parallel, positioned directly next to each other and collecting the WiFi access points' signal strength measurements. The operating system for all the devices was Android OS.

The first problem that became apparent was that the devices do not have the capability to conduct really high frequency measurements. The delay for each scan was approximately 1 second, 3 seconds and 5 seconds for corresponding devices listed above.

For that reason, of course the data collection ability for the devices were different and the number of actual live measurements taken with corresponding devices also differed, ranging from 284 measurements for the fastest phone to 106 measurements.

As concluded from the experimental results, the average signal strength variance was ranging from 6 dBm to 11.3 dBm and the maximal variance was up to 20dBm over all devices and measurements.

One thing to also consider, is the filtering of mobile hotspots from the data, since they can vary and appear practically anywhere and cannot be used to make accurate assumptions about the location of the individual.

3.2 Mapping by physical sensors

Another approach that was attempted, was the mapping with the use of the various sensors that modern smartphones incorporate within themselves.

These can be real sensors, such as accelerometer, gyroscope, pressure sensor or virtual ones, meaning the sensor is not a physical device connected to the phone, but rather a composition of the data provided by various real sensors, in order to make up a sensor that can provide useful data to the programmer, without having to compose everything from scratch.

Examples of virtual sensors are linear acceleration, which is acceleration from which gravity is excluded, or rotation vector, which can calculate the actual rotation of the phone based on sensors, such as accelerometer and gyroscope.

3.3 Positioning algorithm

These sensors can provide data about how the user has moved the phone. Provided we make some assumptions on how the phone is held, we can estimate where the user has moved and which way the user is looking now, i.e. the heading.

One of the main components therefore is the distance travelled. One way to estimate/calculate it, which was considered was the double integration of the accelerometer values. This proved to be quite impossible and was quickly discarded. Future improvements by adding particle filters or Kalman filters may improve this was of localization, but is left as future research aspect.

Another approach is to use the pedometer algorithm. Pedometers allow to count the steps that a user has taken and taking into account the sensors present in the modern smartphone, then extracting the number of steps from for example the linear accelerometer sensor is rather simple. Taking into account, however, that different people still walk differently, some sort of calibration mechanism still needs to be put into place.

Since the pedometer outputs the step count, then if we can estimate the step length, then by that one can extract the path traversed, provided that a heading is also provided. The estimation can be achieved with an initial calibration step, which would ask the user to walk a predefined distance (e.g. 5 meters) from which it can be calculated, based on the number of steps measured, how long is the average step of the individual. Another way to improve it, is to also let the user define a threshold value for a step. Since some individuals are more light on their feet than others, then this can provide an even better estimate on the steps and therefore also the traversed path length.

A relative heading can be extracted from the rotation vector sensor, meaning that the heading of the phone points to for example north and when the phone is turned, the sensor outputs a value relative to the north. This is not exactly what is needed, because of course the person need not start moving in relation to the north, but more logically in reference to some location and heading within a building, for example an arbitrary corridor.

When the relative heading is known, we know the estimated step length and we can determine when a step occurs, then we can do a simple calculation of the users next location, from

sin(heading) = y'/stepLength
cos(heading) = x'/stepLength,

where heading is the heading of the user, stepLength is the estimated length of the step and x' and y' are the additions to the current (x,y) positions on the map.

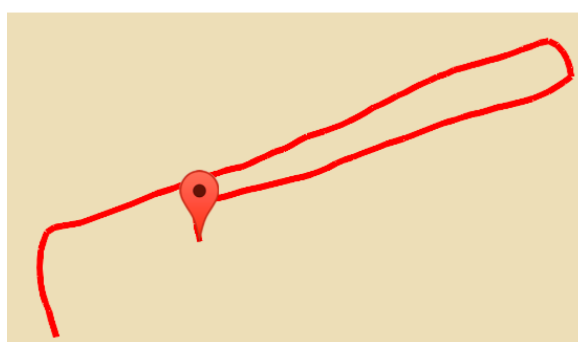

Figure 4: Mapping error estimate

The mapping error estimation reference figure can be seen in figure 4. The path that was traversed was from point A to B to A, meaning from a location to another and then back again, by traversing the same path again, just in a different direction. The errors are present, but not huge, with a rate of about 2-3m for the specific measurement.

3.3.1 Calibration

The calibration mechanisms include three different modes of both autocalibrate and manually insert a calibration value. The modes are step detector, step length and floor pressure.

Step detector autocalibration works in the way that it tells the person to walk forward 10 steps and then tries to come up with the optimal threshold to make up the step level.

Step length asks the user to walk 5m and using the step detector can provide the length estimate of the step.

The final output, as seen on figure 5, summarizes the output provided by the map, as the path travelled, current location and heading, slider to improve the heading offset and selection of the floor from the dataset.

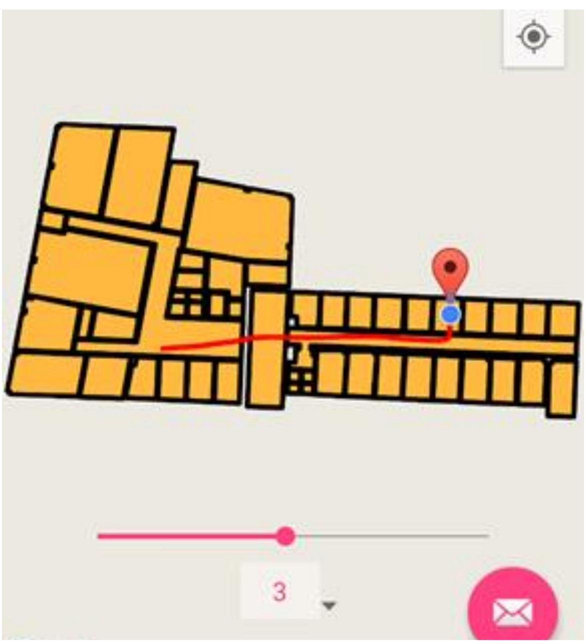

Figure 5: Final map outout example

4. Future improvements and interests

Floor pressure works in a way that it reads an initial averaged value of the pressure, which is assumed to be the current floor, then the user has to walk to the next floor and upon the pressure measurements of the next floor the pressure difference between the floors can be easily calculated. This then allows to automatically change the floor as soon as the user arrives on the next floor. Some more optimizations have to be put into place to make the check more robust, to know if the user is moving up or down. Without this optimization, the map can be forever fluctuating in between floors, if the user is located at the difference point of the floors.

Due to the nature of the measurements provided, the sensors must be given an initial heading and also a starting point, which are both defined by the user and therefore expect the user to give a location and heading within the building, most likely at the time of entry and near some well-defined point that can be easily detected from the map by the user himself/herself.

Future improvement approaches might include fixing some calibration points with WiFi within the building and when the user walks near these points, the location will be corrected, based on the new values.

Another way to improve, is to tie some locations to places that the user will go to, for example exhibits in a museum and near every exhibit there will be a corresponding RFID tag. Upon scanning the tag, user will be presented with information about the exhibits, to motivate the user to actually use the RFID tags. Upon using active RFID tags, the values and locations could be estimated similarly to beacons within a small area.

Research into various filtering approaches, such as the Kalman filter or particle filter is still undergoing development and is taken as a future research aspect.

5. References

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[2] "Indoor Positioning Using WLAN Fingerprinting with Post-Processing Scheme," [Online]. Available: http://www.tuit.ut.ee/sites/default/files/tuit/arvutitehnika-thesis-msc-2014-puussaar-aare-text-20140528.pdf. [Accessed November 2015].

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