SPATIAL MODEL FOR INDOOR UNKNOWN INFRASTRUCTURE WITH BUILT INFORMATION

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ABSTRACT

While navigation systems for outdoor environments are readily available, navigation within buildings still poses a challenge. Maps used as filters to deal with position estimation errors, such as the signal noise of global positioning system (GPS). Although a precise geographical position is easily obtained via GPS technology in outdoor environments, GPS signals are known to have noise and exhibit errors when used by pedestrians in urban areas or in indoor areas such as shopping malls. However, creating an indoor floor plan for an anonymous building poses technical challenges. This paper presents accelerometer based method to enable mapping indoor environments, where global positioning system (GPS) is not available. To identify the localization, authors used 3-axis accelerometer equipped smartphone. User carries the phone while walking around in a building, and pre-process raw data from sensors to determine the user's context. Authors present the algorithm to guide the user to find the destination using accessible database. A practical calibration technique is also proposed to handle the error in aligning the sensing axis with coordination axis. In the case where motion acceleration is not negligible compared with the gravitational acceleration, a compensation technique to extract gravitational acceleration from sensor data is proposed. Also it demonstrates a methodology to overcome challenges while using smartphone as the only sensor equipped device and create the map with the help of the localization information. Experimental results of human motion capturing are also described with graphics.

Keywords: Accelerometer, indoor map, indoor navigation, localization, motion capturing

1. INTRODUCTION

In today's mobile computing era various kind of map information are an essential part in location based services. Many available localization technologies have low coverage or only work in a specific environment. Global Positioning System (GPS) has been accepted very well in consumer devices recently. It works well when a good view of sky is available. However the signal levels from the satellites are already very low in strength when they reach the surface of the earth and it gets extra attenuated when indoor environments are being considered [1]. GPS-enabled devices are quite valuable and will become more and more widespread, but it is clear that many systems require another technology to meet the coverage and accuracy demands of applications. Infrared, ultrasound and Bluetooth localization systems work well indoors, but deploying these technologies to the wide area is either cost prohibitive or not technically feasible, for example, due to infrared interference from the sun. The wide adoption of Wi-Fi enabled mobile devices and rapid deployment of Wi-Fi access points make Wi-Fi localization attractive, but again all the buildings are not rich with Wi-Fi infrastructures. Considering the problem scenario, authors present a mobile based solution to navigate in an unknown indoor environment.

In order to achieve the proposed solution following objectives are investigated:

1. **Infrastructure less indoor localization**: Discuss a method free from technologies such as Wi-Fi and GPS.
2. **Database handling**: Built Information Model which contains information about the environment. Each point represent as a co-ordinate on a Cartesian plane.
3. **Manually add location points to Java OpenStreetMap [3]**: Create an indoor map rich with built information lately used as a platform for indoor navigation.

4. **Indoor navigation**: A method integrated with Java OpenStreetMap to guide a person in an indoor environment.

2. METHODOLOGY

This section discusses the proposed methodology and detailed comparison on research results.

2.1 Infrastructure less indoor localization

Modern smartphones include many different sensors. In order to determine the position of a smartphone in an indoor setting different sensors had to be taken into account, because no single sensor is accurate enough for required task. One of the sensors that have been analyzed is the accelerometer. The accelerometer returns the actual acceleration of the smartphone split into the components x, y and z in the unit m/s^2 as shown in Figure1. The raw sensor data is not directly applicable for map creation. They need to be processed first in order to get measurements suitable for the purpose.

2.1.1 Integration approach for accelerometer

With an ideal accelerometer the speed ($\underset{v}{\rightarrow}$) of the device could be calculated by integrating the accelerometer data ($\underset{a}{\rightarrow}$) over time (Equation no.1). Then the position ($\underset{s}{\rightarrow}$) of the device could be calculated by further integrating the speed over time (Equation no.2). But this approach has some drawbacks. The data of real accelerometers have small tolerances which are summed up when integrating. Subsequently, the already erroneous value of the speed must be integrated again to obtain the position, resulting in no longer usable data. For example, if the device is at rest, small errors are integrated resulting in a small value of speed. This small speed is interpreted as a change of position even if the device actually is not moving.

$$v(t) = \int_0^t a(t)dt \qquad (01)$$

$$s(t) = \int_0^t v(t)dt \qquad (02)$$

The other drawback is that the device can be arbitrarily oriented in space. However, for compensating the influence of gravity, it is indispensable to know its direction. The direction of gravity cannot be determined exactly because the orientation of the device can only be calculated based upon accelerometer values. But only if the device is at rest, the accelerometer data can be used to determine the orientation of the device. As soon as the device is accelerated, the direction of gravity is not identifiable anymore.

Because of these two problems it is not possible to calculate the current position of the device by integrating the accelerometer values over time. With the use of a gyroscope the second problem could be solved, depending on its accuracy. However, the first problem would remain unchanged or even get worse because of the error imposed by the gyroscope. An error in the measurement of the orientation of the device results in an erroneous compensation of the influence of gravity. This will be further results in an increased error in the acceleration measurement.

2.1.2 Magnitude calculation for accelerometer

Because the device can adopt an arbitrary pitch and roll, the individual axes are not bound to the world coordinate system. X points towards east, Y points towards the magnetic north and Z is perpendicular to the ground at the device's current location and points away from the center of the Earth.

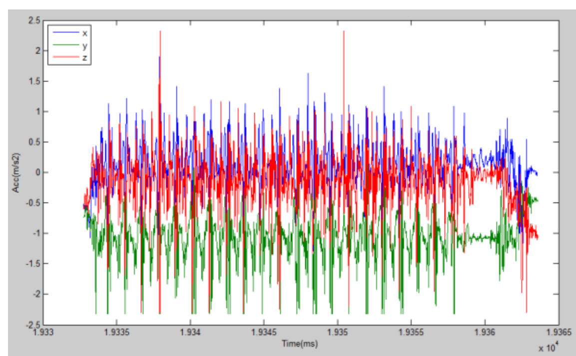

Figure 1: Individual axis varying with time

The gravity (g) could for example be mapped exclusively to the z-axis or as well to the y and x-axis, depending on the alignment of the device. Because of this condition, steps cannot be measured based upon one particular component. We have to find a way to reduce the relevant acceleration to one quantity on which the calculations for counting steps could base upon (Figure 2). The relevant acceleration consists of the measured acceleration minus gravity. The magnitude of the resultant vector is defined as (Equation no.3):

$$|a_{res}| = \sqrt{\{a_x^2 + a_y^2 + a_z^2\}} \qquad (03)$$

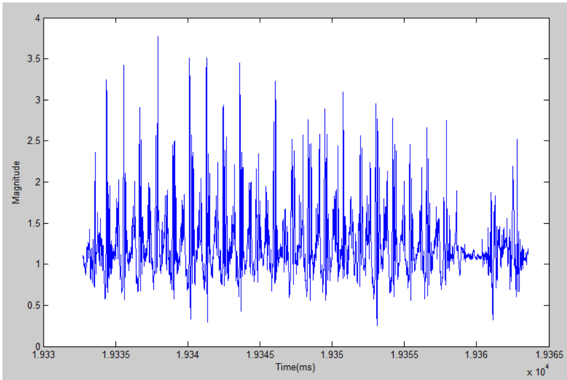

Figure 2: Magnitude varies with time

The main issue with this method is that the magnitude of the resultant vector primarily represents changes parallel to the direction of the gravity. Small changes in the acceleration ($\Delta a \ll g$) orthogonal to the gravity are only represented by a small percentage in the resultant vector; $|a_{res}|$ is not influenced by Δa for $\Delta a \ll g$ where $|a_{res}| - |g| \approx 0$ as depicted in Figure 3.

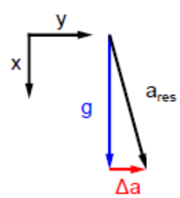

Figure 3: Small change in acceleration orthogonal to the gravity

While changes in the acceleration parallel to the gravity (Figure 4) are completely represented by the resultant vector; $|a_{res}|$ is directly influenced by Δa for Δa where $|a_{res}| - |g| = \Delta a$.

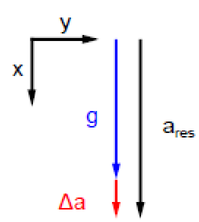

Figure 4: Small change in acceleration parallel to the gravity

2.1.3 Applying low-pass filter for the accelerometer

To eliminate the dependence of the direction of gravity authors introduced a way, low pass filter the individual components. The three low pass filtered components represent gravity as long as the orientation of the device is not altered. As soon as the device is turned around an axis, the three low pass filtered components are delayed. The size of this delay can be influenced during the design of the low pass filter. If the delay is short enough it will not disturb the recognition of localization points. The three low pass filtered components can then be subtracted from the raw accelerometer readings. The outcome of this subtraction is a vector which represents the accelerometer readings without the gravity component. If just the magnitude of the newly calculated vector is considered, a further problem is implicated, because the magnitude does not contain any information about the direction of the acceleration. This means, if the magnitude of the acceleration remained fixed at the same value but the direction of acceleration changed, this change could not be detected.

For example, if the device describes a circle in space without turning around the axes of the device, the vector of the measured acceleration describes a circle as well. However, this is not recognizable if only the magnitude of the resultant vector is observed, because the lengths of the vectors are the same. This means, that the device can accelerate in different directions without a change in the magnitude of the acceleration vector. Therefore, it requires another method to reduce the three acceleration components to one quantity, without the loss of information about the direction of acceleration.

3. RESULTS

Since this research totally based on how the smartphone sensors work and its accuracy, eventually noise becomes a critical factor. For testing purposes authors have used a square like test bed and Figure 5, 6, 7 and 8 depicts how the generated graph distorted with the increasing noise level gradually. When applying low-pass filter to filter out an accurate range of localization readings, increasing noise level causes applying more weight on movements. It implies that the noise factor cannot be completely eliminated. Each and every test bed is considered as a spatial model which holds spatial points of the environment. But authors have realized the accelerometer itself is not enough to obtain a more accurate spatial model. This base stage tests lead authors fusing accelerometer along with the gyroscope to obtain a better spatial model with lesser noise effect on spatial points.

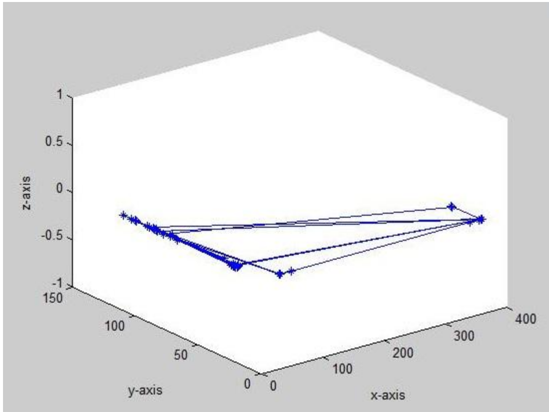

Figure 5: Device localization map, noise level 20

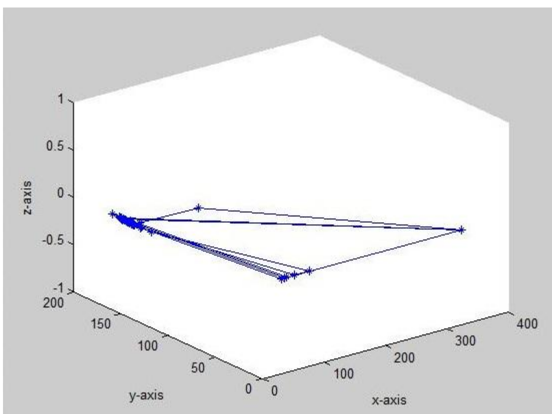

Figure 6: Device localization map, noise level 30

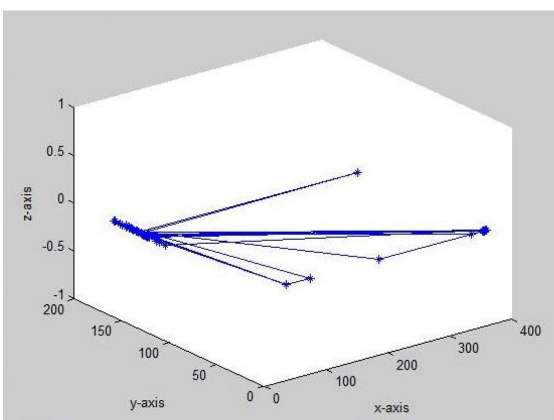

Figure 7: Device localization map, noise level 35

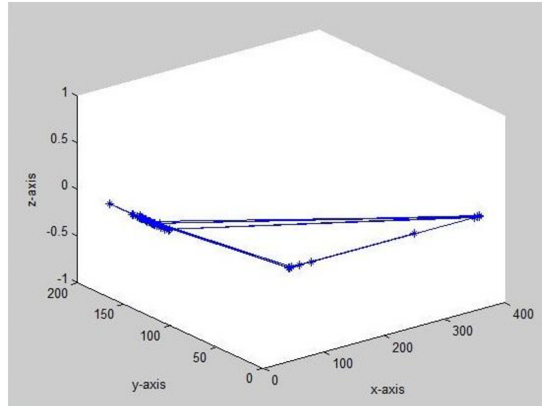

Figure 8: Device localization map, noise level 40

4. CONCLUSION

This paper has been discussed the primary stage of authors' attempt towards building a spatial model only based on smartphone built-in sensors. The test results proved that the accelerometer itself cannot accurately localize a spatial point but it has the capability of identifying the action, triggering a human step. Authors have introduced that we can completely rely on a person's footpath to build up a basic map of an unknown infrastructure yet we need to have a strong spatial model rich with more accurate spatial points. The next step of this research will be fusing the accelerometer's ability of identifying a triggered human step with the 3-axis gyroscope where this combination introduces advanced motion sensing such as user acceleration, angular velocity and rotation rate.

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