Indoor Localization in a Novel Way: Using Distributed Wireless Vibration Sensors

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Abstract

Locating things indoors in the absence of the Global Positioning System (GPS) is a problem researchers have been trying to solve since 1992. Various approaches have been tried like infrared[1], ultrasound[2], WiFi signal strength[3], cameras[4], QR codes[5]. However, all of them have some or the other drawback prohibiting them from being widely adopted as the indoor positioning system of choice for the masses. In this paper, we present a unique approach to indoor localization, one that has not been tried before. We use a distributed system of vibration sensors, sensitive enough to capture the floor vibrations, produced when someone is walking, to localize the footsteps. We do time difference of arrival analysis of the vibration signal between two vibration sensors to get an estimate of the location of the footstep. Initial experiments have given us a localization error of 0.2 metres, much lower than many of the aforementioned systems, thus showing great promise. This approach is also scalable, inexpensive, non invasive of privacy and does not require the user to wear anything.

1. Introduction

For localization, the Global Positioning System (GPS) has long been established as the standard. However, when it comes to locating people or objects in closed spaces, the satellite signals required for GPS to work do not reach thus making it difficult to use GPS in such scenarios. Knowing the precise location of someone or something indoors enables a wide range of contextually aware applications. With an indoor positioning system, one could enable navigation within large closed spaces such as universities, offices or shopping malls. It could also be used to analyze space occupancy patterns for efficient space management. There are niche use cases too, like knowing the locations of patients and caregivers within a densely populated hospital to ensure timely care service or preventing the elderly from getting lost outside their old age homes. Owing to so many possibilities, no wonder that researchers from both industry as well as academia have been trying to solve the indoor localization problem since a long time.

2. Background

The first indoor positioning system was Active Badge[1] developed at At&t Cambridge in 1992. It used infrared waves to estimate position. The user had to wear a badge which would emit infrared waves which would be picked up by a receiver. All the data would then be sent to and processed by a central server. Since the system used infrared, the major drawback was that sunlight and florescent light could interfere with the signals rendering them useless. Then came Active Bat[2], which used the ultrasound time of flight lateration technique. It still needed users to carry a device emitting ultrasound and the receivers had to be mounted on the ceiling. The drawbacks of this system were that ultrasonic equipment is very costly and the solution was not scalable. A research group at Microsoft came up with RADAR[3], which used Wifi signal strength on mobile devices to estimate location. That was however not very accurate and did not work in places where there were many walls blocking the Wifi signals. More recently, people have tried cameras[4] and QR tags[5] but those have not been very promising either. While cameras are expensive and privacy invasive, scanning QR tags successfully depends on the ambient lighting conditions and the angle from which they are being scanned. For a more in depth comparison of indoor localization solutions, please refer [6].

3. Motivation

As can be seen from the above sections, Indoor Localization is a problem researchers have been attempting to solve way back since 1992. Various approaches have been tried but each had its limitations prohibiting them from being widely adopted like GPS. Our group at CMU has been working with vibration signals from vibration sensors since sometime and initial work on identifying footsteps from floor vibration signal and localizing them has shown promise[6][7][8]. So our motive was to expand on that work and develop a real time indoor localization system consisting of a distributed system of these vibration sensors communicating with each other wirelessly. Such an approach to indoor localization is unique and has never been tried before by anybody in the world. We feel this approach is scalable in the sense that many such vibration sensors can be deployed with ease. These sensors are also inexpensive and unlike some other solutions tried before, do not invade the user's privacy. Unlike Active badge or Active bat, this approach also does not require the user to wear or carry anything thus making it convenient to use. We describe our system in detail in the following sections.

4. System Overview

Our system consists of sensor nodes, beacon node, and a central server which runs signal processing algorithm to detect and localize step events. Our system can localize the footstep position between these two sensors. When one person walks, vibration waves are produced on the surface and propagated to these two sensors and waves arrive each sensor in different time according to the footstep position. We use this time difference of arrival to estimate the footstep position. Therefore, it's important to have accurate and synchronized timestamp in these two sensors. For this reason, our system has beacon node to broadcast timestamps to all sensor nodes.

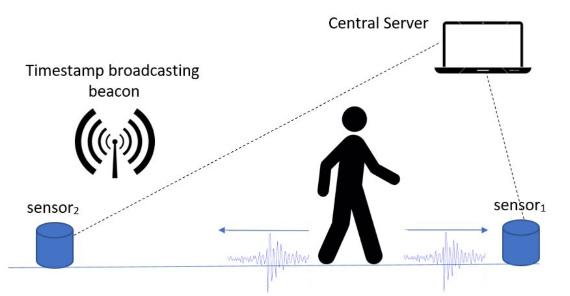


Fig. 1: System overview

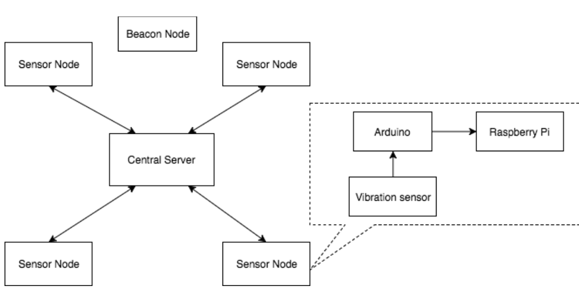


Fig. 2: System block diagram

For sensor node, we use Arduino board, vibration sensor, and Raspberry Pi. Arduino board periodically senses the the value of the vibration sensor and forwards the result to Raspberry Pi which transmits the result to the central server over WiFi. The central server runs the signal processing to detect and localize the step events. In addition, a beacon node is implemented to synchronize the timestamps between sensor nodes.

5. System Implementation

5.1. Sensor node and time sync

Each sensor node periodically collects the the value of the vibration sensor at sampling rate 6 kHz and forwards the result to the central server through HTTP with each file containing 5kB over WiFi.

Fig. 3: Vibration sensor (geophone)

The sensor node integrates Arduino board, amplifier circuits, Raspberry Pi, vibration sensor, and radio module as the following figure.

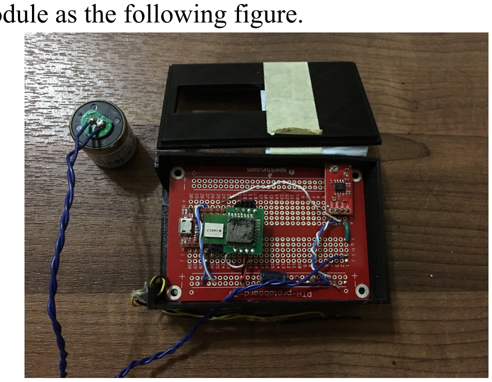


Fig. 4: Sensor node

The beacon node broadcasts timestamps to all sensor nodes every second and communicates with them through the radio module on each sensor node.

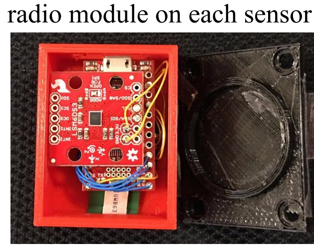


Fig. 5: Beacon node

5.2. Wireless Transmission

Raspberry Pi continuously reads data from the Arduino board through the serial port. Every time it reads a 5 kB buffer, the Raspberry Pi first saves the buffer into a local file and then sends the file to a central server out over HTTP protocol. Time for transferring each file is less than one millisecond. The central file server is implemented on flask

framework and collects data files from two sensors concurrently. Files from different sensors are saved into different folders.
A parser program also runs on the central file server, which will parse the binary data from the sensor into timestamp and vibration data. The parsing result will then be pushed into a message queue for real-time signal analysis.

5.3. Signal Processing

i. Velocity Calibration
To estimate location of footstep with time difference of arrival approach, we need to calibrate the velocity of the vibration wave for the given surface, since the velocity of the wave varies as per the surface.

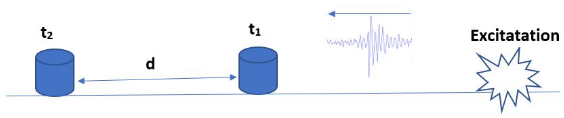


Fig. 6: Excitation away from 2 sensors

Through making an excitation away from 2 sensors, we can measure the distance between 2 sensors and the time shift when this signal arrives to 2 sensors. Then we can calculate velocity using equation:

$$V = \Delta d / \Delta t$$

ii. Step Detection
The raw sensor data contains both noise and footstep events. To identify footstep events from a signal consisting of non event data, we need to obtain a range of non-event data only first. This non event data (noise) is modeled as a Gaussian distribution. Then we will extract signal energy from the signal within a time window. Through moving this time window over the whole signal, we will calculate energy for each time window. If the signal energy is beyond 3 standard deviations above the mean of the noise signal, we consider it a potential footstep event. The size of the time window and threshold for standard deviation are found out experimentally.

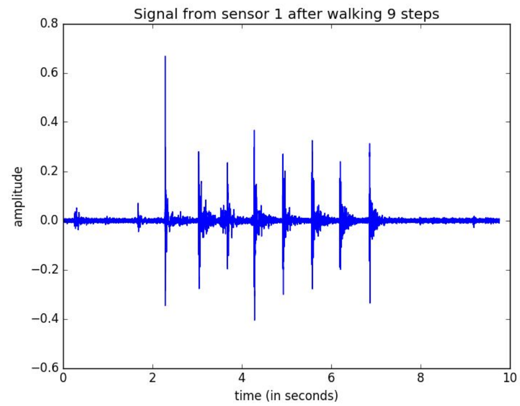
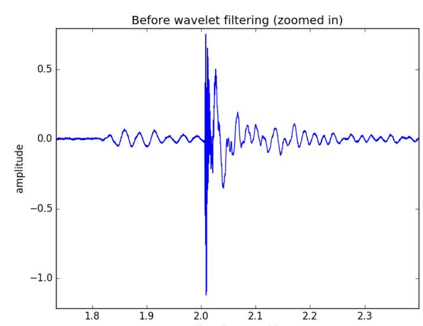


Fig. 7: Signal from sensor 1 after walking 9 steps

iii. Wavelet Filtering
In the time difference of arrival, accuracy was super sensitive to the time difference (to the order of 10^{-4} seconds). Our algorithm does this time difference between the peaks within the footstep signals. So finding peaks accurately is extremely important. During the course of our experiments, we realized that due to the dispersion effect of the surface, these peaks within individual footstep signals can be caused by different frequencies. Thus their time difference would not always give us accurate results. Hence, we needed to perform wavelet filtering where we extract specific frequencies from the signals and then do time difference of arrival between the peaks thus giving us much more accurate results. The before and after effect of wavelet filtering can be seen from the following 2 figures.



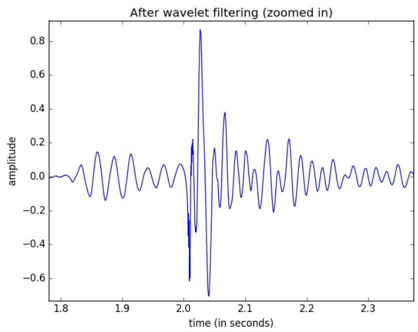


Fig. 8: Sigal before / after wavelet filtering

iv. Localization - Time Difference of Arrival

Since we already measure the calibrated velocity for the hallway, we can use time difference of arrival approach to estimate location of footstep event. Through measuring the time shift between the peak of 2 signals, we can calculate Δd based on the velocity:

$$\Delta d = V * \Delta t$$

$$\Delta d = distance\ from\ footstep\ to\ sensor1 - distance\ from\ footstep\ to\ sensor2$$

Based on the fact that the distance between 2 sensors, we can calculate estimated location:

$$Estimated\ Loc = (Distance\ between\ 2\ sensors + \Delta d)\ /\ 2$$

6. Evaluation of results

6.1. Error Rate

To evaluate the accuracy of our system, we do indoor localization of footsteps as a person walks. It was set up in the hallway with marble floors in Building 19 in CMU. In this experiment, 2 sensors were kept 10 feet apart. One person walked from one sensor to another sensor with 6 steps. These 6 steps were walked 2 feet apart. Velocity calibration was done beforehand (as in 5.3). Through using time difference of arrival approach, we can calculate estimated location for each footstep events. The result is:

Time Difference (microseconds)	Estimated Location (Meter)	Ground Truth (Meter)	Error (Meter)
-8580	0.51313269	0	0.51313269
-6608	0.739951144	0.6	0.139951144
-3700	1.07442785	1.2	-0.12557215
4360	2.00148502	1.8	0.20148502
8724	2.503430118	2.4	0.103430118
11901	2.86884707	3	-0.13115293

Table 1: Test result.

From the table, we could find that the average error rate in this experiment is 0.202 meters, which is much better than the error of 1 meter for which indoor localization systems are judged to be very good.

6.2. UI

For user interface, we used Django as the web framework and present the result in a view of Marauder's Map. The UI will continuously fetch the latest data of step coordinates and the corresponding timestamps from one specific file, and then update the footstep shown on the floor plan with variable time intervals depending upon the timestamps.

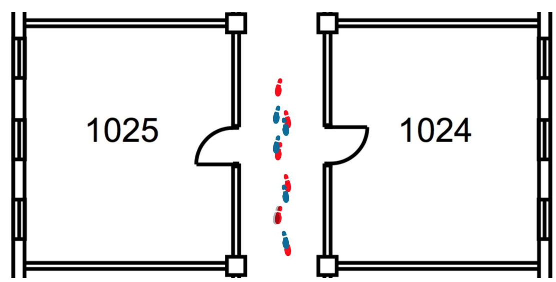


Fig. 9: Evaluation of indoor localization at Bldg 19 hallway. Blue − calculated results, red − ground truth.

7. Conclusions

Our project attempts to solve the indoor localization problem in a novel way with the real-time analysis of vibration data and achieves an error of 0.202 meter between ground truth and output of our algorithm. This is very promising. There are several parts of our system. Two vibration sensor nodes are used to collect data. Beacon is responsible for time synchronizing. The central server receives the data files and parses the raw data into analyzable format. Data analyzer moves a sliding window over the data to detect a footstep. Time difference of a same footstep between two sensors and the footstep signal velocity are the keys to calculate the location.

8. Future Work

8.1. Conduct more experiments

For now, we have only a few sets of walking data. More walking data over different surfaces is needed to fully evaluate our system and calculate a more provable average error.

8.2. Two-dimensional localization

With only two sensors, our system can only locate a footstep in one single dimension. We can extend the system into two-dimensional localization by adding another sensor.

9. References

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