Movement localization in indoor environments by means of light and air pressure sensors

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ABSTRACT

Distance-based techniques for localization require large amounts of configuration or complex computations, rendering such systems too expensive for consumer use. Alternative methods such as Radio Signal Strength profiling (RSS) provide a cheap alternative, but these sensors still require fine-tuning. By investigating the use of cheaper and more readily available light and air pressure sensors, this paper will attempt to localize a moving object. This system uses light and pressure sensors to collect data. The system is validated using Thingy:52's but is not specifically tailored to this platform.

Keywords

Cooperative Sensor Localization, Device-free Localization, Movement Detection, Movement Localization, Nuisance Parameters, Sensor Networks

1. INTRODUCTION

Around the world, localization plays an ever more important role in automated systems. From smartphones to automated transportation vehicles, there is a growing need for accurate positioning in a variety of situations. There is already a variety of cheap options available for outdoor uses, but in indoor scenarios, a large investment in specialized materials and systems is often required.

In the field of localization, there are several commonly employed methods. These can be categorized in three distinct groups, *Angle of Arrival*, *Distance based* and *Radio Signal Strength Profiling*.[6] Of these, the second is the most well known and widely employed, as the receivers can be made relatively cheaply. This is the methodology used by, among many others, the GPS, GLONASS and Galileo systems.[5]

Distance-based systems do, however, require a high degree of fine-tuning to achieve reasonably accurate results. The Global Positioning System, as an example, requires that all transmitters to be synchronized to within 40 nanoseconds and can only provide results accurate to 5 meters under optimal circumstances. For fine-grained applications and especially indoor applications, a different method is required.

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Copyright 2020, University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science. As discussed by Vaghefi et al., options based on the radio signal strength profiling (RSS) are a popular alternative because of the low cost of implementation.[7] These sensors are cheaply available and often already present for other reasons. As such, recent research has been more focused on building localization on these sensors.

Traditionally, radio sensors have been used for this purpose as they can easily be attuned to frequencies with little background noise. But alternate sensors such as light or air pressure have only gained attention in recent years.[2][8] These sensors are becoming easier to access as more consumer products are being built with these sensors included.

The proposed system is designed for indoor usage where device-free localization is required. It can be applied, for example, in elderly care. Patients in such facilities are prone to falling and might forget to carry a monitoring device. This system could be employed to warn caregivers when this happens.

This system will not only provide an alternate manner of localization, but it can also be employed in multi-modal configurations. Such systems are often designed to leverage the strengths of its subsystems to achieve higher accuracy than any one single system individually could achieve.

2. RESEARCH QUESTION

As such, the following was formulated as the main research question:

Can the position and movement of an object be determined with light and pressure sensors in an indoor environment?

To structure the research approach, the main question has been split into the following sub-questions.

- **RQ1** How can a single light sensor be used to determine in what direction an object is moving?
- **RQ2** How can a single air pressure sensor be used to determine in what direction an object is moving?
- **RQ3** Can a combined light and pressure sensor be used to achieve higher accuracy in determining what direction an object is moving?
- **RQ4** How can multiple sensor pairs be combined to accurately localize a moving object?

2.1 Hypothesis

It is expected that visible light behaves similarly to radio signals, as both are a form of electromagnetic radiation. But, its application isn't as straightforward as RSS strategies with an actively emitting target. The object will have an influence on light propagation, but this is expected to be a complicated relationship, and how exactly it has an influence is to be investigated.

A similar note should be made for pressure. Instead of the constant source signals that are used for radio-based localization, the air pressure only changes when the target is moving. And, when the object stops moving, the pressure readings will return to ambient levels.

Overall, the system is expected to work with a reasonable degree of accuracy in indoor situations.

3. BACKGROUND

3.1 Non-Invasive Localization

In certain situations, it can be preferable to track objects without attaching a device, either because the trackers might get lost or because the volume of objects is too high. This was previously done using video cameras, but this has several big disadvantages. First is the privacy violations such an always active camera system might cause. It is not hard to imagine malicious actors gaining access to the system and causing disruptions in the system or sharing the collected data with unauthorized parties.

Second is the fact that the subject might move outside the monitored area. In certain situations, this can lead to targets getting displaced or diverted. This limitation is, however, not exclusive to video-based systems.

As such, more and more researchers are looking towards radio technology to provide broader coverage. For example, Zhang et al. surround an area to be monitored with cheap radio transceivers and use machine learning to determine whether a target is in the monitored area and where it is situated.[9]

3.2 Thingy:52

To validate the methodology proposed below, the Thingy:52 will be used as a testing platform. It is a cheap, low-powered sensor prototyping platform which can be connected to using a Bluetooth Low Energy connection. Its firmware, as well as sample applications, are available under an open-source license. It offers a wide array of sensors, but for this research, only the air pressure and light sensors will be used.

4. RELATED WORK

4.1 Localization

The 2017 survey performed by Paul et al. categorizes methods of localization in three distinct groups, *Angle of Arrival, Distance based* and *Radio Signal Strength Profiling*.[6] In past decades, distance-based methods got the most interest, but recently the RSS profiling option has gained more attention. It offers a simpler and cheaper implementation than its alternatives.

But, RSS based solutions also require more computational complexity. An array of parameters must be initialized correctly for the system to work, and these values differ per location. Hu et al. described a method of RSS profiling where these values are not known, so-called *blind* RSS.[3] These methods attempt to estimate the transmission power and background noise when they cannot accurately be determined, such as with hostile or non-cooperative targets.

Furthermore, as pointed out by Martin et al., noise reduction systems often make subtle assumptions that might not necessarily be true.[4] Chief among these is that the signal-to-noise ratio in RSS based techniques is close to 1, i.e. that there is comparatively little background noise for a given signal. They point out that this assumption can be wrong, especially when working with a non-cooperative target.

4.1.1 Device-free Localization (DfL)

Device-free localization is often used in situations where it is undesirable or impossible to attach transponders to the objects being tracked, either due to volume or privacy concerns. Commonly, device-free RSS-based localization techniques require a training phase before they can start to localize objects. This is done by positioning the object in a spot, recording the received radio fingerprint, and repeating this for all possible locations.

Recently, however, research is trying to reduce the required amount of initialization in device-free localization. One avenue being pursued are model-based techniques based on radio tomography.[1] These systems collect data by having sensor-pairs monitor a narrow slice of the space for disturbances. If such a disturbance is found, the exact position can be determined by intersecting multiple of these slices.

5. METHODOLOGY & APPROACH

In order to properly answer the question posed in this research, there are several key steps. First of which is the collection of data from the Thingy:52's using a Bluetooth Low Energy connection. The collected data is stored in an InfluxDB database, which also facilitates some rudimentary analysis. To facilitate the later analysis step, it is important that the collection rate is sufficiently high, preferably at 15Hz or higher.

Thereafter, the next step is to build an understanding of how the sensor readings change in response to different environmental factors and how they respond to different scenarios like moving towards or away from a sensor. This data will be collected by placing a small cuboid (6cm by 6cm by 4cm) in front of the sensor and moving it in various directions using fishing line.

Proper analysis of the data might require noise reduction or normalization. Common methods to do this include running averages and the removal of high-frequency signals. It is important here to take the work by Martin et al. into account when developing the noise reduction strategy.[4]

It is planned to feed this cleaned up data to a neural network to classify movements. The network will get to consume the last 20 observations of all four channels (*red*, *green*, *blue*, *clear*) and outputs one of three states (*towards*, *away*, *no movement*.) The amount of hidden layers, as well as their sizes will be determined empirically.

Last is the development of a system capable of using the aggregated data from multiple sensors to provide actual movement localization. This will leverage a Bayesian model to combine the different readings. This accounts for both the possibility a sensor picks up too much background noise, as well as the possibility that sensor readings are conflicting.

5.1 Testing & Validation

The system will be validated in two manners. First is a small scale testing setup of 1 by 1 meter. This will not have walls as to reduce the interference from reflection. This setup is illustrated in figure 1. The primary light source will be placed above the setup at a height of roughly 40 cm, but it should be noted that reflected light from other



Figure 1. Schematic drawing of a validation setup without walls.

sources cannot be completely mitigated and can influence the reported values of the sensor.

This setup is used for testing the individual localization as well as cooperative localization. In the first case, the object will be placed at the center of the setup and moved along and perpendicular to the primary axis of a selected sensor. When validating the cooperative approach, the object will be placed and moved along the primary axes as well as in composite directions.

The second setup is more akin to a real-world application. This testing will be performed in a 3.5 by 3.5 meter room where the sensors will be placed against the wall. This will cause more reflected signals, but might also prove to yield a more clearly defined change in pressure.

In both setups, the accuracy of the solution will be determined as the mean squared error of three distinct elements of the movement vector: the direction, magnitude and origin.

6. **RESULTS**

6.1 Data Collection

As discussed earlier, the first step in the development of this localization system is the reduction of noise on the reported sensor values. The readings of the light sensors were directly usable, as their signal to noise ratio is between 10^2 and 10^3 . This is illustrated in figure 3. As such, it was decided to not implement a noise reduction strategy here.

Figure 3 also shows that the reported light levels might still change, even if there is no clearly identifiable reason for the increase or decrease. In this case, the object was lit using overhead lighting, but the shifting weather conditions still had an effect on the reported light levels.

The reported values of the pressure sensor proved, however, quite noisy. The spread of values was significantly larger than what was expected from a small moving object, 0.2 hPa and 0.05 hPa respectively. A sample of the reported pressures is illustrated in figure 4.

While the method proposed by Martin et al. would be

able to filter out the noise in such scenarios, it would require a large number of data points to be collected of the same situation.[4] This means the noise reduction strategy they developed is only able to accommodate low-frequency changes. This is not the case on the scales the Thingy:52 is usable as a moving object has a high-frequency signature.

6.2 Detection using Single Light Sensor

As part of the hypothesis of this paper, we postulated that the relation between light levels and how an object is moving would be complicated. The expectation was that reflected light of the object and the shadow it cast could negate each other under the right circumstances. This assumption turned out to be wrong, however. The effect of reflected light, while certainly an important consideration, was significantly smaller than the effect caused by cast shadows.

As such, the detection algorithm saw a decrease in its complexity. While originally it was planned to use a neural network, the simplified version compared the difference between a moving average and the last observation. If this value exceeded a set value, it would be classified as movement. The direction of change then indicated the direction of movement relative to the sensor. (i.e. moving towards or away from the sensor.) After empirically testing various sizes of objects, it was determined that this trigger value should be between 50 k and 100 k.

The light sensor of the Thingy:52 reports light levels in terms of four distinct channels, *red, green, blue* and *clear*. As such, the above-described method of detection can be applied to each channel individually. The detection of an object moving towards or away from the sensor are illustrated in figures 5 and 6 respectively.

6.2.1 Movement Detection

To properly detect and classify movement, it is important to acknowledge the fact that a single channel can occasionally classify data incorrectly. To mitigate this, the individual channels need to be aggregated, which can be done in two distinct manners.

First is the option to aggregate the raw data and then classify its result. This can be done using simple addition or via more complex algorithms that take the relative change in value into account.

The other is to determine movement based on individual channels and aggregate the results afterwards, for example by using a majority vote algorithm. This approach does, however, have one large disadvantage. If the object is illuminated using monochromatic light, it might become undetectable for some or all of the channels.

However, in most real world applications, light sources are not monochromatic. Taking this into account, and considering the limited time-frame during which the system was developed, it was decided to use the simpler majority vote approach.

Should this algorithm result in a tie, the data will be classified as *no movement*. This means that a situation where two channels report *movement towards* the sensor and the other two report *movement away* will still be seen as *no movement*. While this might seem counter-intuitive, this was done as there is no clear alternative option.

6.2.2 Object Ranging

Accurately ranging the moving object proved to be too large a challenge for this paper alone. The intuition to determine how far an object is that a nearer object will



Figure 3. Reported light levels in lux in a static environment.

Table 1. Statistical analysis of pressure			
	No movement	Towards	Away
Min.	1010.91 hPa	1011.00 hPa	1011.03 hPa
Q_1	1013.29 hPa	1013.24 hPa	1013.23 hPa
Med.	1013.58 hPa	1013.33 hPa	1013.33 hPa
Q_3	1014.49 hPa	1013.51 hPa	1013.52 hPa
Max.	1031.53 hPa	1031.47 hPa	1031.43 hPa
Avg.	1015.90 hPa	1015.95 hPa	1015.81 hPa
Var.	5.73 hPa	6.17 hPa	6.02 hPa
Skew.	2.15 hPa	1.95 hPa	2.05 hPa
Kurt.	2.71 hPa	1.82 hPa	2.23 hPa

cast a larger shadow and thus decrease light levels more. This assumption does indeed hold in static environments where the source of light is of fixed luminance.

In real-world situations, this assumption cannot be made. There are a large number of events that can cause interference when attempting to range an object. For example, other moving objects can cause complex reflective patterns, which are difficult to account for. But also the time of day and local weather patterns should be accounted for as they can change how much impact the shadow of an object has.

6.3 Detection using Single Pressure Sensor

As described earlier, the data collected of the pressure sensors proved to be too noisy to accurately detect a moving object. As is illustrated in figure 4, the spread of the returned values was significantly larger than the signal a moving object might cause.

Using simple filtering strategies such as moving averages was also determined to be ineffective. This is due to the fact that a movement is of short duration and causes a lowfrequency change. The filters were unable to compensate noise while maintaining a detectable signal. It is yet to be determined if this noise can be reduced by using more accurate sensors.

6.4 Detection using Combined Sensors

As previously discussed, the data collected from the air pressure sensor seemed to be unusable. To validate this, the data from earlier experiments was analyzed again alongside the data from the light sensor. The data was separated into three partitions according to how the light sensor had classified it.

The numerical summaries and four central moments were

compared between samples of stationary objects and those moving towards and away from the sensor. For all these samples, no statistically significant difference could be found in the numerical summaries or central moments at a level of confidence of 95%. The found values can be seen in table 1.

6.5 Detection using Multiple Sensor-pairs

Once a single sensor can detect movement with a reasonable degree of certainty, it is possible to combine multiple sensors to classify movements in two dimensions. In this research, four sensors were placed pairwise along the major axes in opposite directions. This setup is illustrated in figure 1. Using trigonometric functions, the global movement of an object could be determined.

This was validated by moving an object along the major axes as well as across a diagonal path. The object was placed 25 cm from the centre point and pulled in a straight line until it had passed over the centre point and was 25 cm away from it, as illustrated in figure 10. The results of these tests are shown in figures 7, 8 and 9, respectively. These figures show that the system is able to detect movement towards or away from a sensor, but isn't able to detect objects moving along a diagonal path.

This lack of detection is due to the relatively small changes in the light levels reported by the sensors, which is illustrated in figure 11. In turn, these small signatures ensure that none of the sensors are individually able to detect the object, which means that the developed cooperative aggregation strategy also is not able to classify the movement correctly.

Due to time constraints, the system was developed with the restriction that all sensor-pairs would be aimed towards and equidistant from a centre point. This meant that only a rotational offset needed to be taken into account when combining reports. While more was less complex to implement, it is not always possible or desirable to meet this requirement. Furthermore, it is also not grounded in any technical limitations. As such, the system can be expanded to work in more situations than the current implementation is able to.

A more elaborate system, where not only the rotation but also the position of each sensor can be configured, should be able position a moving object in a space instead of only determining the direction of movement. This can, for example, be accomplished by creating sectors in the monitored area.



Figure 4. Reported ambient pressure in hPa in a static environment.



Figure 5. Individual channel detection when moving towards the Thingy:52.



Figure 6. Individual channel detection when moving away from the Thingy:52.



Figure 7. Cooperative movement localization of an object moving along the X axis in positive direction.



Figure 8. Cooperative movement localization of an object moving along the Y axis in positive direction.



Figure 9. Cooperative movement localization when moving along a diagonal.



Figure 10. Schematic drawing of movements used to validate cooperative localization.



Figure 11. Sample of reported values in lx of a sensor when moving an object along a diagonal.

7. DISCUSSION

7.1 Air Pressure Sensor Noise

As discussed earlier, the reported values of the Thingy:52's air pressure sensor show a spread of 0.2 hPa under static conditions, which can be seen in figure 4. This effect has two causes, but it is yet to be investigated how much influence each has.

Firstly, the Thingy:52 is built using cheaply available sensors. Such sensors are commonly less accurate and will show a higher deviation from ground truth than their more expensive counterparts. As such, using a different sensor platform might yield more usable air pressure readings.

But secondly, what humans perceive as completely static air is rarely truly stationary. The effects of Brownian motion can cause small but measurable changes in pressure when this might not be expected. It should thus be investigated if and how much influence these effects have and how they can best be mitigated.

7.2 Thingy:52

The Thingy:52 is promoted as a prototyping platform, which is reflected in the build quality of the device. Besides the earlier discussed issues with the air pressure sensor, this also manifests itself in the range and field of view of the light sensor. While the exact range and field of view varies from device to device, an average is illustrated in figure 12.



Figure 12. Schematic drawing of the field of view of a Thingy:52's light sensor.

The range in which all tested devices noticed an object is illustrated as the smallest of the two sectors. This extends three-quarters of a meter from the device and covers a 25-degree arc from the centerline. The larger sector illustrates where a Thingy:52 might pick up on a change, the probability of which is largely dependent on how reflective a given object is. This range extends to approximately 1 meter from the device and spans about 45 degrees from the centerline. It should be investigated if and to what extent this field of view can be extended or made wider.

7.3 Limitations of the Implementation

The current implementation has several limitations, the two most important will be discussed here. Firstly, the developed system does not require a specific amount of sensor nodes, instead, it can be configured to work with any amount. It does, however, require that all nodes are directed towards a single point and that they are all equidistant from that point. This assumption does not hold in all cases, areas that are significantly longer than wide, such as hallways currently pose an issue.

Secondly, the system assumes a single moving target is being monitored. This assumption was mainly made to reduce the complexity of this exploratory research, but it cannot hold for applications in the real-world. To use the same example of a hallway again, it happens often that multiple people are walking down the same hallway. The current implementation would be unable to handle such situations.

7.4 Future Work

This paper opens various avenues to further research, which can be summarized into the following three categories.

7.4.1 Increase Target Variety

The developed system was built under the assumption that the target is non-reflective, which meant that the signal intensity would decrease as an object moved closer to the sensor. This was done to develop clearer fingerprints of a moving object. Future research could investigate if and to what extent a reflective object causes a different pattern than those illustrated in figures 5 and 6.

7.4.2 Decrease Sensor Noise

The reported values from the light and air pressure sensors of the Thingy:52 contain a certain element of noise, which can be seen in comparing figures 2 and 3. For realworld applications, the assumption of a clean and relatively static environment cannot be made. As such, future research could look into how to reduce the noise caused by such situations.

7.4.3 Extend Field of View

As described earlier, the area in which a Thingy:52 can reliably detect a moving object is quite limited. This means the developed system is only applicable to monitor small areas, which is undesirable for real-world application. Future research could investigate how this range could best be extended.

8. CONCLUSION

In this research, the possibility of using a light and air pressure sensor to localize a moving object was investigated. It was shown that a simple detector can be built to detect moving objects using a light sensor. Localization using the air pressure sensor of a Thingy:52 proved unfeasible due to a low signal to noise ratio. A statistical analysis was preformed into the possibility of multi-modal localization, but this proved unsuccessful. It was also shown that a cooperative approach to localization can increase the accuracy and reliability of such systems.

As a result of this research, we conclude that it is feasible to localize movement using multiple light sensors. The possibility to do this using pressure sensors could neither be confirmed nor ruled out.

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