Unsupervised Learning for Indoor Localization and Mapping

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Introduction

Indoor localization is a problem within indoor environments due to GPS inaccuracies, which are insufficient for providing good position estimates inside a building. Navigating inside a building is also a complicated task because there is usually no floor plan available. Our objective is to gather data from smartphone's sensors (accelerometers, gyroscopes and magnetometers) in order to identify key landmarks and create a map of the building that will help improve on techniques for indoor localization.

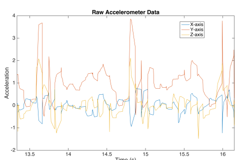


Figure 1. Raw Data

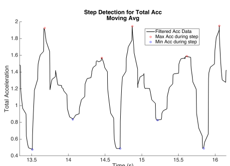


Figure 2. Step Detection

Step Detection

A step detection algorithm was used to generate a more accurate user displacement estimation. This method relied exclusively on accelerometer data. In order to accommodate for erratic orientation and attitude shifts of the phone during a walk, we calculated the norm of the accelerometer data. We further filtered out low frequency disturbances in the data by applying a moving average over a 0.2s time span. At the onset of each trial, a 'Step threshold' was calculated based on the variance in accelerometer data during the users standing state [2], [3]. A step was recorded at each timestamp at which the accelerometer data crossed the Step detection threshold along with the associated acceleration peaks. Based on the peak to peak acceleration amplitude at each detected step, we deduced the approximate length of each step. Erroneous steps that were detected due to high frequency noise occurring at the threshold were discarded using a 0.3s blanking window following the onset of each step detected.

EKF

In order to estimate the orientation of the smartphone, we implement a quaternion based extended Kalman Filter (EKF) from the outputs of the accelerometer, gyroscope and magnetometer [4]. In addition to the in-line bias estimation of some of the sensors, we take into account the potential local disturbances of the magnetic field and the effects of body motion. The Extended Kalman filter is a version of the Kalman filter that works for non-linear problems. Instead of using a fixed matrix for the state and observations equations, we are computing the Jacobian matrix to linearize about an estimate of the current mean and covariance.

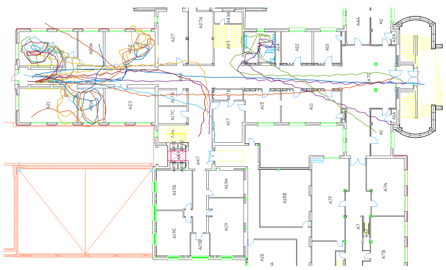
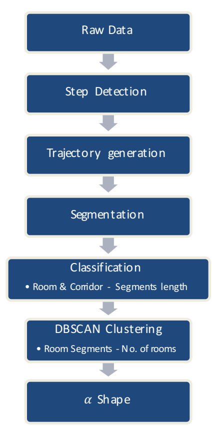


Figure 3. Trajectories

Framework [1]

For each recording, we run the step detection to get each step and its length while extracting the heading. Then we generate the trajectory based on those values. Further, we create segments that gather consecutive steps moving in the same direction. If the value is above a threshold (45 degrees), a new segment is created. We compute parameters (length of the segment, average time spent per step, coordinates of the center of the segment) for each segment that is used to perform classification.

The segments are then classified based on their length that allow us to distinguish between corridor and room segments. Based on the room segments extracted, we cluster them using Density Based Spatial Clustering of Applications with Noise (DBSCAN). The number of clusters represents the number of rooms detected. Finally, an alpha-shape algorithm generates the shape of the rooms detected based on the clustering .



Results

The length and step estimations obtained during step detection yielded low error values that were sufficient for computing reliable trajectories. The average error obtained by differentiating between left and right-footed steps was more accurate and may be used to improve future results.

	Experiment			Actual		Error		
	Steps	Total Length		Steps	Total Length			
		By Footing	Averaged			Steps	By Footing	Averaged
Trial 1	64.0	57.1	62.5	65.0	58.7	1.54%	2.76%	6.4%
Trial 2	64.0	57.2	50.7	64.0	58.7	0.00%	2.53%	13.7%
Trial 3	65.0	59.5	64.7	65.0	58.7	0.00%	1.35%	10.2%
Trial 4	65.0	57.8	61.2	65.0	58.7	0.00%	1.55%	4.3%
Trial 5	63.0	57.7	63.5	64.0	58.7	1.56%	1.75%	8.2%
Trial 6	65.0	57.6	60.3	65.0	58.7	0.00%	1.89%	2.7%
Trial 7	70.0	57.0	61.6	71.0	58.7	1.41%	2.90%	4.9%
Trial 8	71.0	52.7	56.8	70.0	58.7	1.43%	10.26%	3.3%
					Average	0.74%	3.12%	6.70%

Table 1. Accuracy result for Step Detection

The results for EKF was unstable, failing to converge. Possible reasons that could explain this are the different reference frames and also the parameters on how we model the errors. If the initialization of the EKF is not right, (parameters or initialization values), the EKF will not converge. Despite this, we were able to draft a map that detects some of the building structures.

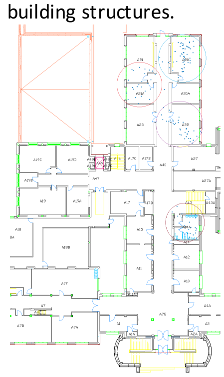


Figure 4. Clustering

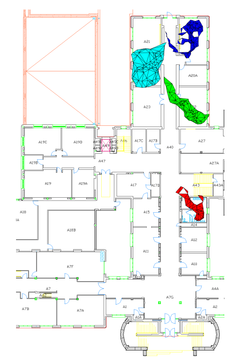


Figure 5. α shape map

Conclusion

We created a framework that is able to process recordings and create an indoor floor map by clustering the segments extracted from the trajectories. Future work to improve the rough map can be done by improving the heading estimation using the EKF algorithm, classifying landmarks such as stairs, elevators and organic signatures based on the sensor values to improve the trajectories generated. It will be interesting to see how the framework will scale up with more data and different users.

References

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