Thesis Results

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Candidate's Declaration

Acknowledgements

Abstract

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Done partially in other files

1.1 Motivation

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Done partially in other files

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3 Problem Description

To develop and evaluate a high accuracy tracking system on a modern smartphone using sensor fusion techniques.

4
Groundwork

Before implementing the system, some groundwork was done regarding the available data:

4.1 Wifi Signal Strength study

The behaviour of the wifi signal strength distribution for a stationary laptop and smartphone was analyzed to characterize the input wifi signal.

4.1.1 Short term duration

Figure 4.1 shows the variation of signal strength of the closest AP for a smartphone placed within a room in a NON-LOS configuration.

4.1.2 During a thunderstorm

Figure 4.2 shows the variation of signal strength of the closest AP for a smartphone placed in a room in NON-LOS configuration.

4.1.3 7 day study

The Wifi AP RSSI values were monitored over a 7 day period (Jan 5 2011 - Jan 13 2011) from room S-152 and the resulting signal strength data was analyzed.

As you can see in Figure 4.3, the signal strength distribution is highly non-gaussian. This kind of distribution makes Kalman filters unsuitable for use as the assumptions of gaussian (linear) distribution of input variables is unsatisfied.

Figure 4.5 doesn't show such a pronounced non-gaussian nature whereas Figure 4.4 shows more leanings towards a non-gaussian distribution.

Figure 4.6 is the time domain plot of the signal strength samples. As you can see, the samples can be spread over a large domain even if the sample times differ by a couple of

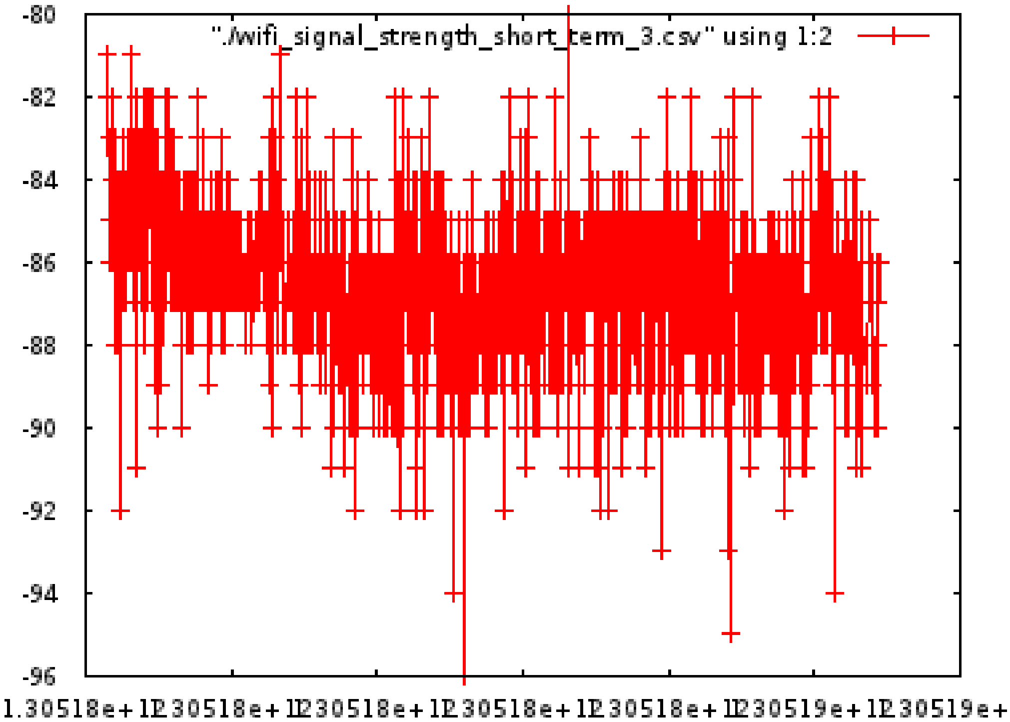

Figure 4.1: Variation of RSSI for closest AP.

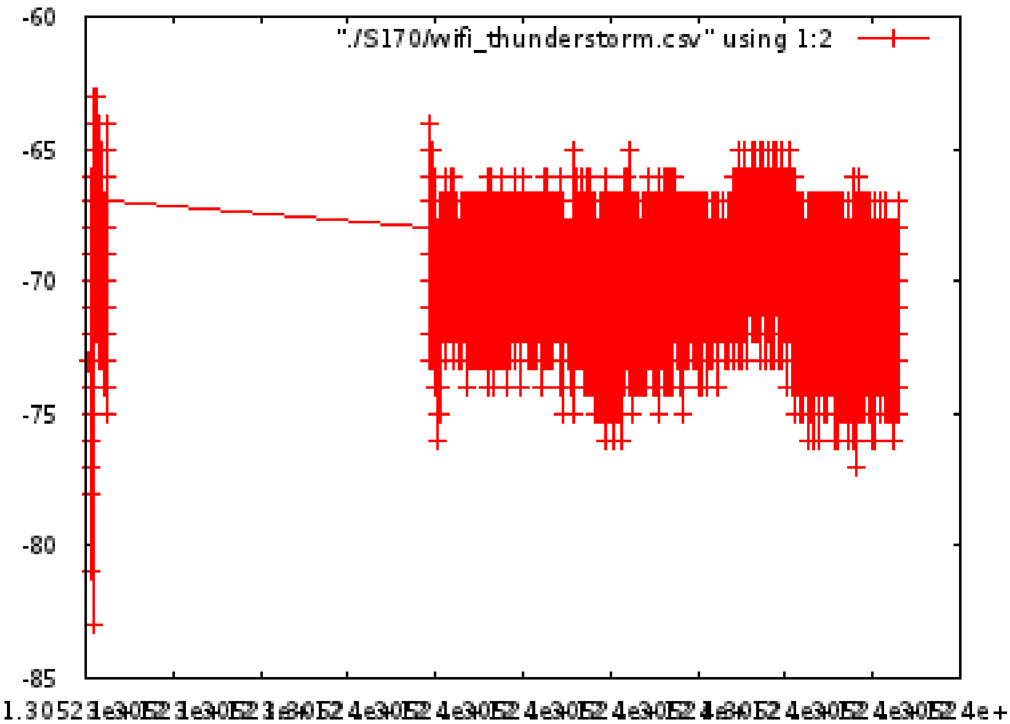

Figure 4.2: Variation of RSSI for closest AP during a thunderstorm.

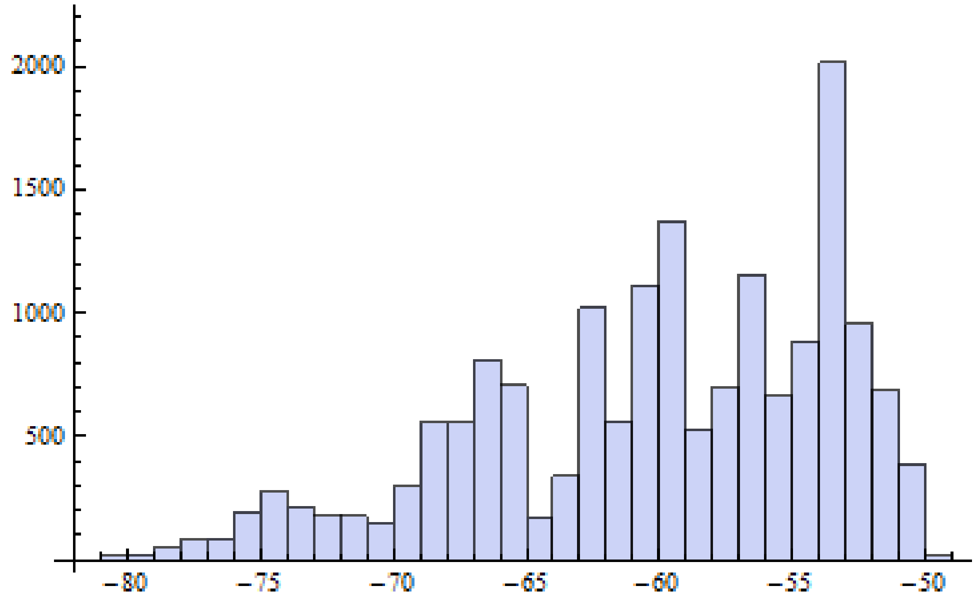

Figure 4.3: Distribution of RSSI values for the closest AP (00:1C:F0:CB:EC:92)

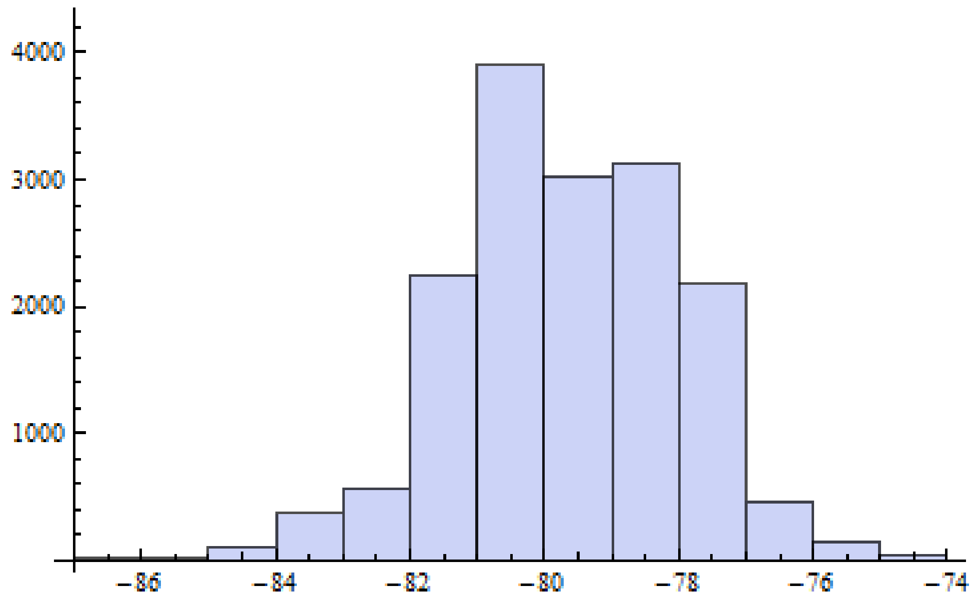

Figure 4.4: Distribution of RSSI values for the AP near S-170 (00:1C:F0:CB:EC:95)

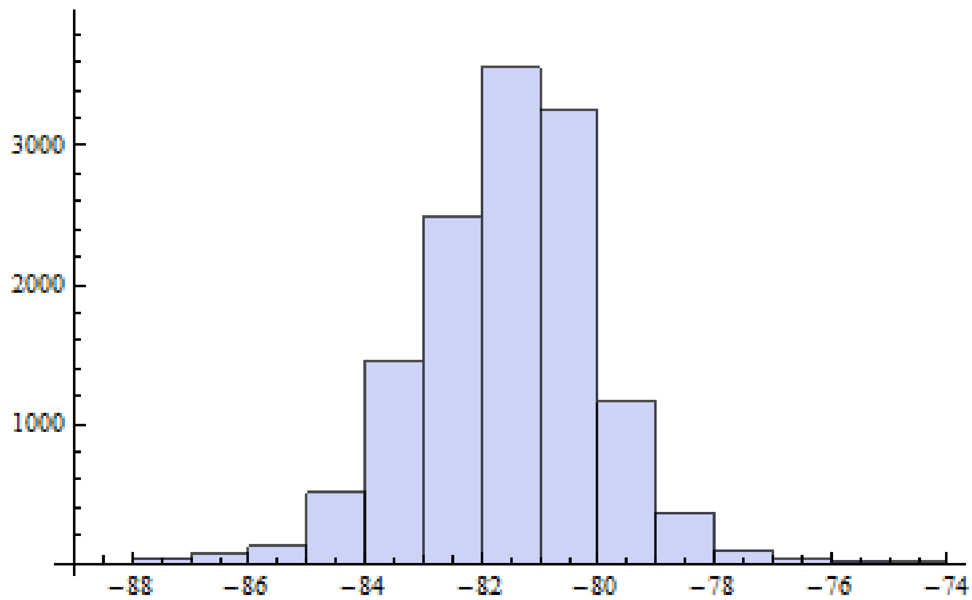

Figure 4.5: Distribution of RSSI values for the AP near S-159 (00:19:5B:77:A5:EE)

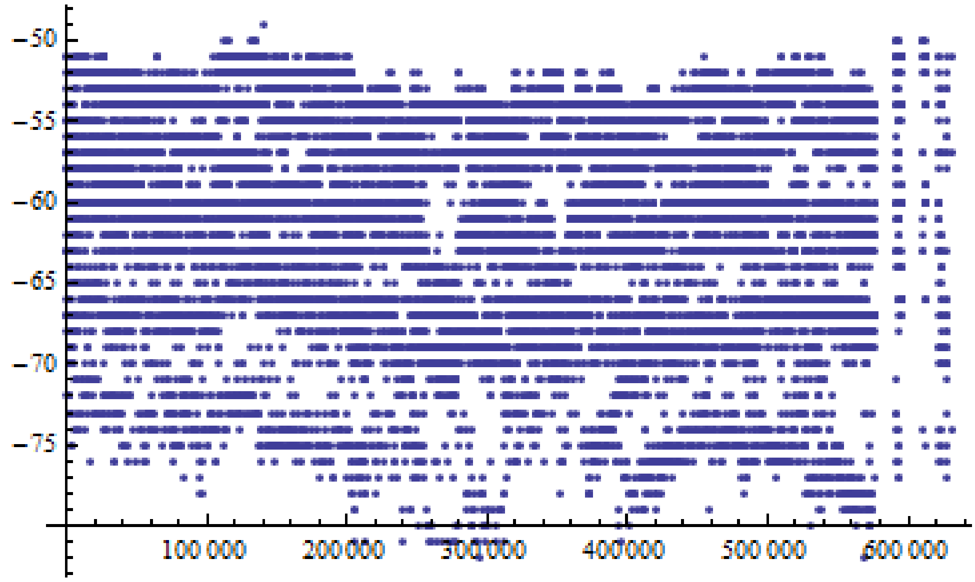

Figure 4.6: Point plot of RSSI values for the closest AP (00:1C:F0:CB:EC:92)

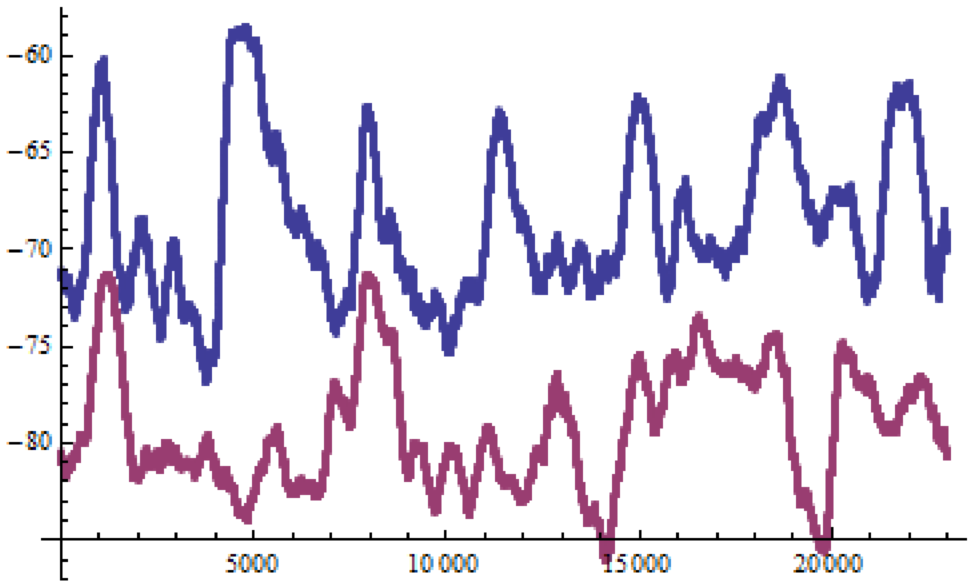

Figure 4.7: 3 hour moving average of RSSI values

hours. Thus we can safely conclude that the input wifi signal is a highly noisy source of information.

4.2 Effect of motion on signal strengths

To analyze the effect of motion on the RSSI values from the APs, a simple walking test was done along a corridoor. The variation of RSSI values seen from the APs in the corridoor are shown in 4.8.

TODO: Improve figure with more APs and path description.

4.2.1 Inferences

Effect of orientation with respect to AP is important. Signal strength values even in LOS situations don't always behave nicely.

4.3 Wifi Surveying

A $1mx1m$ grid was set up on the ground and wifi readings were taken at 8 different orientations per point on the floor.

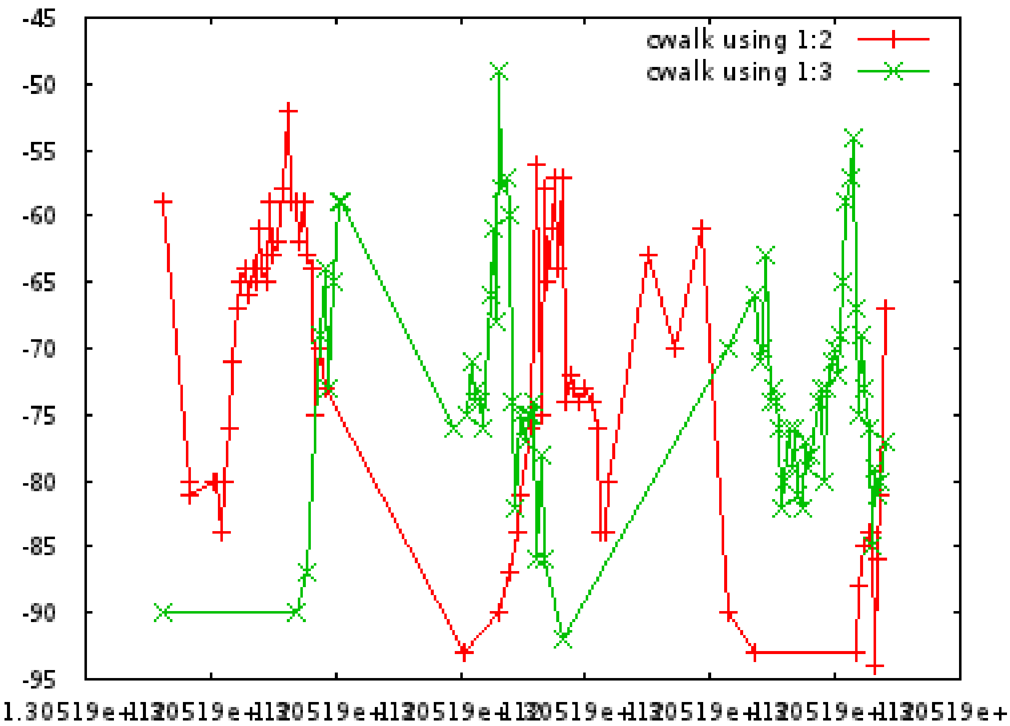

Figure 4.8: RSSI values for APs during a corridoor walk

4.4 Implementation of a KNN based positioning solution for KNN accuracy

A KNN based location system was implemented to test location accuracy. This was work done as part of the project. Results are included here.

Table 4.1: Performance of KNN based indoor positioning system

	Mean Error $\bar{e}$ (m)	σ_{error} (m)	$\bar{e} + 2\sigma_{error}$
$K = 1$	2.8	2.7	8.2
$K = 2$	2.8	2.7	8.2
$K = 3$	2.7	2.7	8.1
$K = 4$	2.3	2.8	7.9

4.4.1 Improvements

Use of SVM is likely to improve the accuracy further at room level. [Redpin]

4.5 Magnetometer

The Nexus S comes with a built in [insert smartphone chip info] MEMS magnetometer. It measures the local magnetic field strength in μT.

4.5.1 Accuracy

The performance is reasonable but the magnetometer has a lot of sensor noise and suffers from sensor bias. For example, rotation of the smartphone through large angles introduces bias in the readings from the magnetometer.

TODO: Insert values for Standard deviation here.

These values are required to determine choice of parameters for the particle filter that will be introduced later.

4.5.2 Bias study

Performing rotations in a slow and steady manner yields good results with little or no bias and sensor lag. See figure 4.13 which shows how the angle measurements behave when the rotated slowly and steadily.

There is only a slight sensor lag and bias visible. However, at steady state, there is sensor noise of approximately 5 degrees present.

4.5.3 Effect of motion

Although the sensor measurements are stable when the device is on a table, the measurements go haywire when the device is in a human's hand. See figure 4.14 - a human is walking along a corridoor and he walks back. The angle measurements of the return

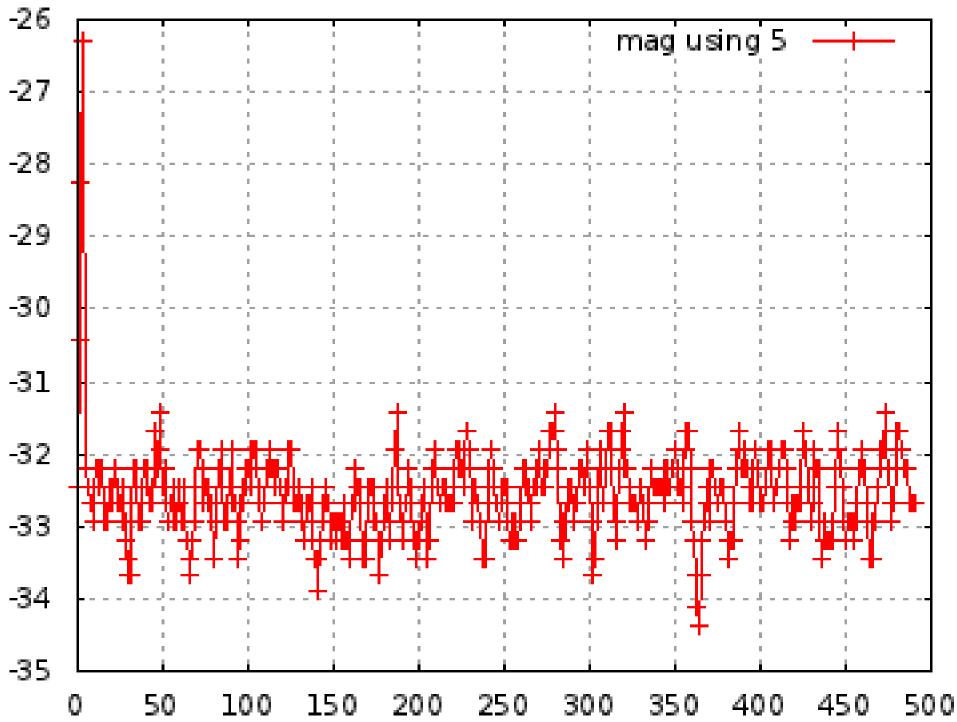

Figure 4.9: Magnetometer readings when device is on a table

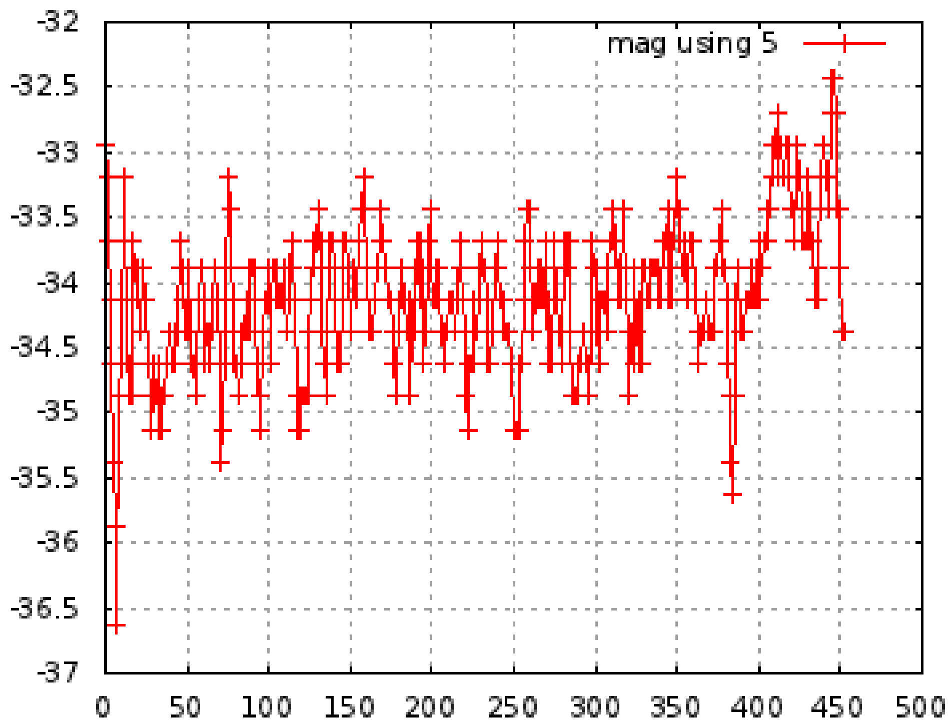

Figure 4.10: Magnetometer readings when device is held in user's hand

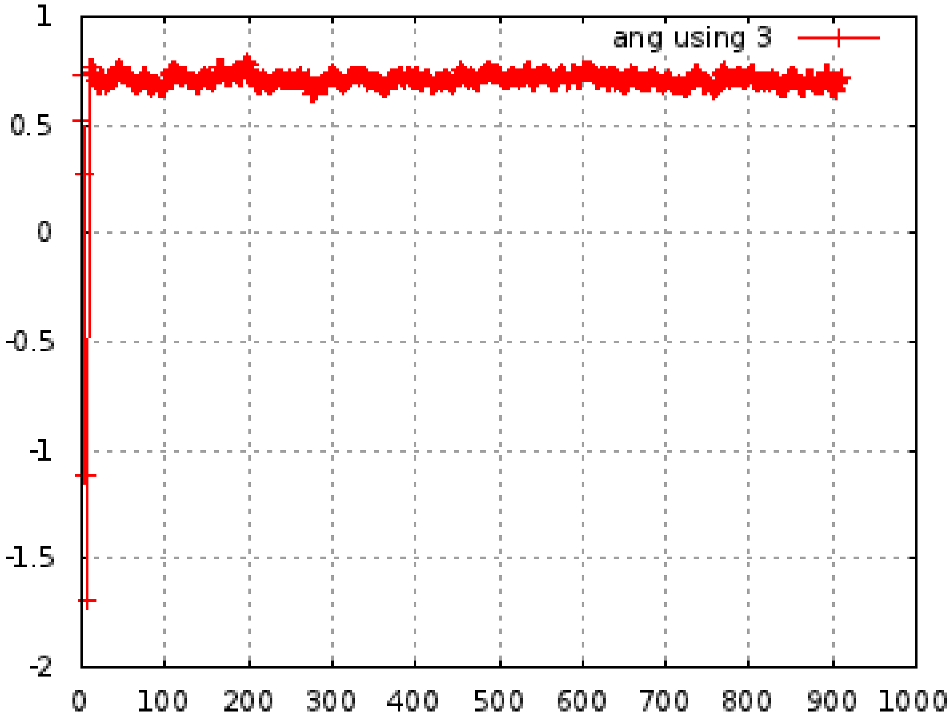

Figure 4.11: Derived azimuth angle when smartphone on table

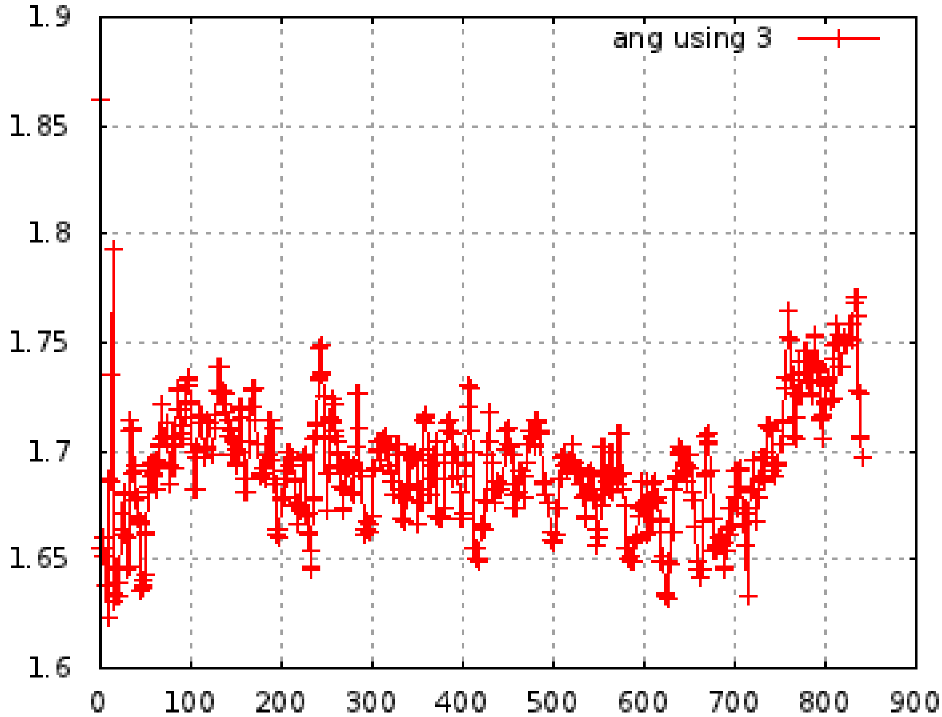

Figure 4.12: Derived azimuth angle when smartphone held in hand

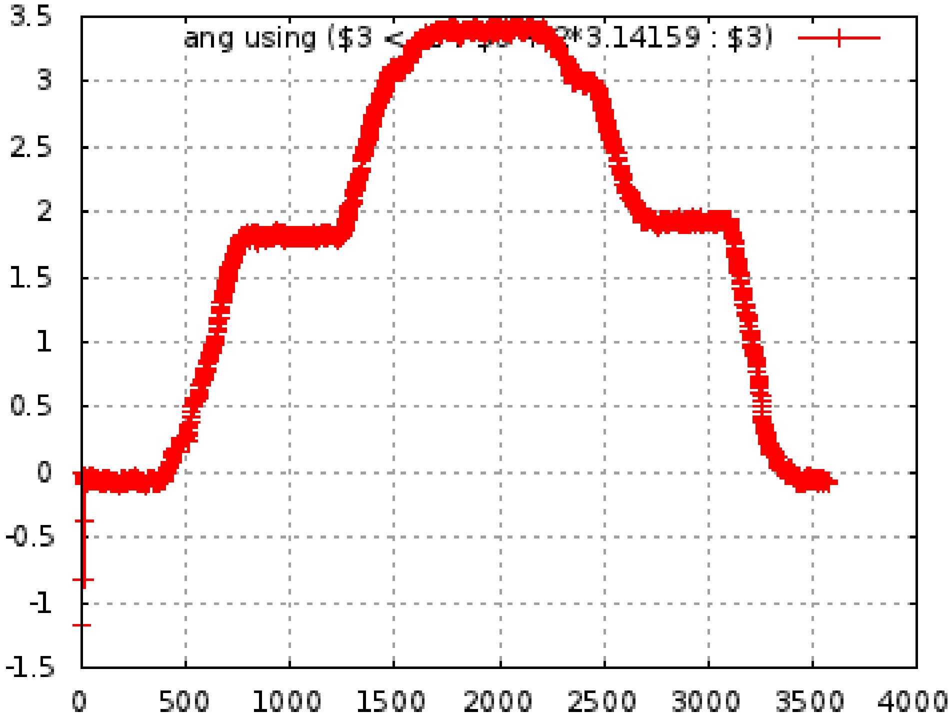

Figure 4.13: Rotation of the phone through 180 degrees with pauses at 90 degrees.

trip are offset by 180 degrees and the two sets of measurements are compared. You can easily see a large variation in the angles due to the motion of the human and the dynamic nature of the environment. Sensor lag and long term sensor value drift is evident in the graph. This dynamic variation of the measurement of the angle from magnetic north introduces error in the inertial navigation system.

4.6 Accelerometer Study

The MEMS accelerometer on the Nexus S was also subject to similar characterization. See figure 4.15.

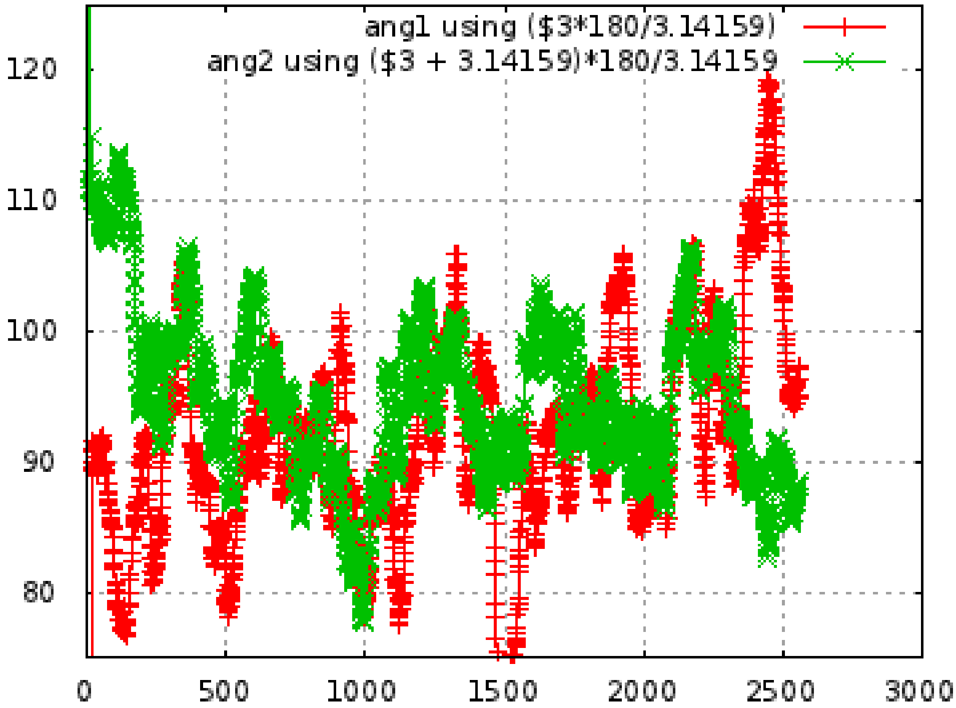

Figure 4.14: Angle measurements when moving in opp directions.

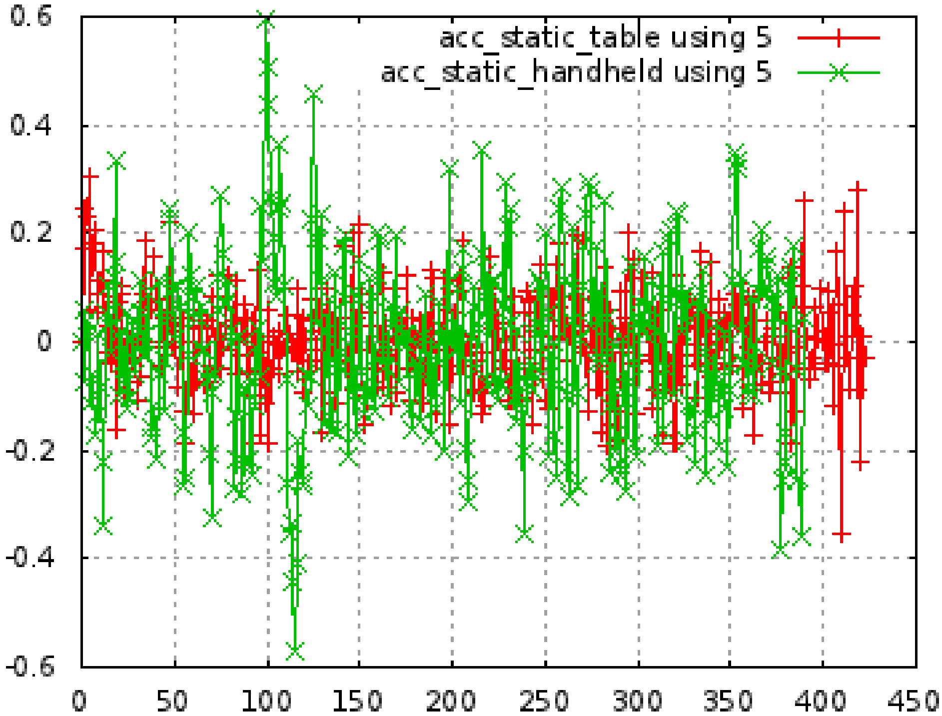

Figure 4.15: Accelerometer Z axis readings when device stationary

4.7 What Doesnt work

Acceleration of the human body is too slow compared to gravity. Simple orientation changes produce high changes in acceleration along axes which are very difficult to filter out. Numerical integration generates errors too quickly. With a high sampling rate, errors balloon. Using the gyroscope for step detection (similar to foot mounted devices [insert reference]) doesnt work.

4.8 Other issues

Sensor noise, instability and bias. Effect of gravity and orientation on readings. Weather.

5

Proposed Method

The particle filter approach described in [ped. Nav.] is adapted to and implemented on the Android smartphone. The onboard accelerometer and magnetometer of the Nexus S are used as inertial navigation sensors. Improvements are made to the algorithm. The performance of the particle filter is analyzed with different parameters and approaches:

5.1 Dead reckoning with step counts

The acceleration of the human body as part of the act of walking is small and very impulsive in nature. The motion of the torso of the body is governed mostly by inertia. Unfortunately, the impulsive acceleration values are small and lie buried in sensor noise. They are virtually indetectible using the MEMS accelerometer supplied with the android device - Nexus S.

To overcome this difficulty, the step count method of [ped. Nav.] is adopted. Under the assumption that step size varies very little over the course of motion of the subject, an inertial navigation system may be created.

5.1.1 Step counting method

The step counting method is described in [ped. Nav.]. However, we take a slightly modified approach.

5.1.2 Noise clamping

The MEMS accelerometer sensor on the smartphone has sensor noise present close to zero. The noise level for the accelerometer was determined to be always less than $0.6m/s^2$. To allow for a reasonable noise margin and provide sufficient cushion for additional noise introduced due to the dynamic nature of walking, we choose a threshold of $1.3m/s^2$. If the absolute value of the Z-axis acceleration sample is less than this threshold, then the sample will be clamped to zero.

As has been determined experimentally, steps taken by a human usually produce a pair of spikes - one positive and one negative with magnitude around $2m/s^2$. By choosing this threshold value, we give maximal noise margin for step detection.

See figure [...] for a comparative estimation of step values versus sensor noise.

5.1.3 Step size detection procedure

Zero Crossings

To detect actual steps taken by the subject holding the device, [ped. Nav.] suggests using zero crossings. However, in the sensor data collected, a number of spurious zero crossings exist (primarily due to sensor noise). However, even after sensor noise is clamped as per section 5.1.2, spurious zero crossings often arise due to variable motion of the subject.

Peak and Valley hunting

Peak and Valley hunting procedure (better than zero crossings) for step detection. Robust to unexpected values.

To have robust detection of steps, a state machine is maintained. The state machine detects a peak and then waits for a trough. Subsequent

An internal state machine is used. The state machine has 2 states and a comparison is made between A_{max} or A_{min} and the sample value that forms the peak/trough whenever state transitions occur.

Table 5.1: State table of the step detection state machine

State	Accelerometer Value	New State	Action
q_0	Positive Peak Detected	q_1	Update A_{max} if peak is of larger magnitude
	Other values	q_0	Ignore
q_1	Negative Trough Detected	q_0	Update A_{min} if trough is negative and of larger magnitude than A_{min}
	Other values	q_1	Ignore

5.1.4 Step Size Estimation

Reference [A. Engineers] provides this empirical relationship between acceleration values and step size.

$$Step - size = C\sqrt[4]{A_{max} - A_{min}} \tag{5.1}$$

The constant C is a scaling factor that is used as a constant of proportionality to scale the step-values to real world distances.

5.2 Sensor fusion using Particle Filters

A background on particle filters has already been given.

5.2.1 Dynamical equations for system

The dynamical equations that govern the system are:

5.2.2 Accelerometer

5.2.3 Orientation

5.2.4 Camera info

For first fix, we use QR codes. They are used whenever subject changes floors too. The QR codes provide information about the map of the floor, the current location and any additional information that is required by the tracking algorithm.

5.2.5 Map Information

5.2.6 Wifi Information

5.3 Accounting for orientation bias and noise

5.4 Accounting for varying step sizes

5.5 Barometer Information

6
Results

6.1 Step detection procedure

6.1.1 Case 1: Using zero crossings

6.1.2 Case 2: Using zero crossings with clamping

6.1.3 Case 3: Using peak detection

6.2 Plain Dead Reckoning

Dead reckoning shows very poor results with the onboard MEMS sensors of the smartphone.

6.2.1 First Fix

Use of QR Codes for first fix

6.3 Plain Wifi Based Positioning

6.3.1 Case 1: Dead reckoning with NN wifi positioning

6.3.2 Case 2: Dead reckoning with KNN averaging

6.3.3 Case 3: Dead reckoning with clamped wifi positioning

6.4 Particle Filter Performance

6.4.1 Case 1: Probability of crossing walls is 0

6.4.2 Case 2: Probability of crossing walls is finite

6.4.3 Case 3: Resampling of impoverished data points with duplication

6.4.4 Case 4: Resampling with introduction of Gaussian noise

6.4.5 Case 4a: Use of averaged data points v/s random weighted data point

6.4.6 Case 5: Accounting for bias in orientation sensor

6.4.7 Case 6: Accounting for step size bias.

6.4.8 Case 7: Simple post processing of output.??

6.4.9 Case 8: Simple heuristics to deal with impoverished samples

(retry, retry with greater inaccuracy)

6.5 Particle filter + Wifi data

TODO

6.5.1 Case 1: Use of Wifi data for accounting for drift errors

6.5.2 Case 2: Use of Oriented Wifi data for accounting for drift errors

6.5.3 Case 3: Use of clamped wifi data for accounting for drift errors

6.5.4 Case 4: Use of area Restricted Wifi data for accounting for drift errors

6.6 Signal Strength Map

TODO if time permits Wifi signal strength map developed using crowdsourced data for use in systems such as RedPin.

6.7 Issues faced

Incorrect step sizes yielded states in which no further progress was possible using data from the inertial sensors. Hence we had to resort to wifi data to get out of the blind spot.

Limited processing power and near-realtime time constraints of operation constrain computational complexity of the solution.

Surveying is the biggest issue in this system.

7 Summary and Future Work

Use and evaluation of SVM as a suitable architecture for the Wifi data. Better integration of information from the camera. Integration of information using a Barometric sensor would be useful for detecting elevation changes. A system for the same is proposed but the experimental results were not obtained.