LUND UNIVERSITY

Sensor Fused Indoor Positioning Using Dual Band WiFi Signal Measurements

Karlsson, Fredrik; Karlsson, Martin; Bernhardsson, Bo; Tufvesson, Fredrik; Persson, Magnus

[Link to publication](#)

Sensor Fused Indoor Positioning Using Dual Band WiFi Signal Measurements

Fredrik Karlsson[1], Martin Karlsson[2], Bo Bernhardsson[2], Fredrik Tufvesson[1] and Magnus Persson[3]

Abstract— In this paper, signal strengths from known WiFi access points are used together with a particle filter to perform indoor navigation. It is shown that more information is obtained by using signals of both 2.4 and 5.0 GHz, compared to using only one frequency. Thus, using both frequencies provides a more accurate positioning. The second contribution is an algorithm where WiFi measurements are combined with pedestrian dead reckoning (PDR), which is based on step counting using an accelerometer and hypotheses of the heading using a gyroscope. This was found to provide further accuracy compared to more conventional methods.

I. INTRODUCTION

A ubiquitous and accurate positioning system for mobile devices is of great importance, due to the large number of applications and services it enables. In most outdoor environments, this problem was solved by the introduction of the *Global Positioning System* (GPS). In indoor or suburban areas however, the GPS signals are often too weak to enable a reliable position estimate. Instead, several other techniques have been proposed. They range from using only one portable device, to attaching several sensors on different parts of the user's body [7].

There are numerous examples where WiFi *access points* (APs) with known locations are used to trilaterate the position of the user. The distance to each AP is often estimated using the signal strength. This can also be done by measuring the time it takes for a signal to travel between the device and an AP, see e.g. [6].

WiFi signal measurements have also been combined with e.g. *pedestrian dead reckoning* (PDR) into sensor fused approaches. In [10], such an example is presented. It is based on a wide range of sensors including accelerometer, gyroscope, WiFi, magnetometer, GPS, barometer etc. Another contribution to this area is presented in [1]. Here, PDR is combined with GPS for an initial position estimate. Then, it uses magnetic field and radio signal strength fingerprinting. One important feature of this procedure is that the algorithm is learning the radiation environment with time, and this is used to detect when the user returns to a previously visited area. Then, errors from the PDR are mitigated. This method is an a example of *Simultaneous Localization and Mapping* (SLAM), where a map of, in this case, the radiation environment is developed during the positioning [4]. The positioning is in turn aided by the map.

[1]Electrical and Information Technology, Lund University
[2]Automatic Control, Lund University
[3]Sony Mobile Communications, Lund

In this paper, two contributions to the field of indoor positioning are presented. The first contribution is an investigation of the behavior of two WiFi frequencies, 2.4 and 5.0 GHz, where their noise is proven to be almost uncorrelated with each other. This is then exploited to develop a WiFi-only trilateration algorithm by the use of a *particle filter* (PF), where the only restriction is that the locations of the APs, and how strong they transmit, need to be known.

The second contribution is based on adding information from PDR to the estimation algorithm, to provide a more accurate position estimate. A step counter is developed using the accelerometer, the gyroscope detects changes in heading and the WiFi signal strengths give information about the position. The concept in this part is that particles with well-approximated headings and positions will get WiFi measurements that are more consistent with the models, and thus be more likely to sustain and multiply. This makes it possible to alongside the position also estimate the heading.

Three different experiments were performed. First, the correlation between 2.4 and 5 GHz signals was investigated. Then, the algorithm was applied without the PDR. Finally, the position algorithm was evaluated using both frequencies, and including the PDR. The smartphone used throughout the experiments was a Sony Xperia Z1.

The resulting algorithm produces position estimates with a mean error of less than two meters. It requires the orientation of the smartphone to be reasonably constant in relation to the user. In this paper, it is assumed that this requirement is fulfilled whenever PDR is used. Nevertheless, it should be mentioned that a version of the algorithm has been developed as an online Java implementation, which is more tolerant to changes of the orientation of the smartphone in relation to the user. In return, however, it produces less accurate estimates with an average error of 3.4 meters.

II. CORRELATION BETWEEN 2.4 AND 5 GHz SIGNALS

To obtain an estimate of the correlation between signals on the 2.4 and 5.0 GHz bands the following method was used. Signal strengths from a certain AP was measured, while the distance d to it was varied. Further, the signal strength was measured while the distance was constant. This was done both in line-of-sight (LOS), and in non-line-of-sight (NLOS). The following 6 series of measurement were taken.

1) d was varied from 2 to 15 meters, in LOS.
2) d was varied from 2 to 15 meters, in NLOS.
3) d was varied from 15 to 30 meters, in LOS.
4) d was varied from 15 to 30 meters, in NLOS.
5) d was kept constant, in LOS.
6) d was kept constant, in NLOS.

Subsequently, the model errors for 2.4 GHz (a) and 5 GHz (b) were computed as the difference between the modeled and the measured *Received Signal Strength Indicator* (RSSI) values. Then, this was used to estimate the correlation coefficient, r_{ab}, between the errors of the different frequencies, for each series of measurement.

The estimated correlation coefficients [2] between model errors of 2.4 and 5 GHz signals together with 95% confidence intervals [3] are shown in Table II.

TABLE I
ESTIMATED CORRELATION COEFFICIENTS AND 95 % CONFIDENCE
INTERVALS FOR MODEL ERRORS OF 2.4 AND 5 GHZ IN THE DIFFERENT
SERIES OF MEASUREMENT. THE CORRELATION DOES NOT SEEM TO BE
LARGE.

Signal path	Estimated correlation, $\hat{r}_{ab}$	95 % conf. int.
1) LOS near AP	-0.10	$[-0.29; 0.09]$
2) NLOS near AP	0.26	$[0.05; 0.44]$
3) LOS far from AP	0.26	$[-0.09; 0.55]$
4) NLOS far from AP	0.24	$[0.04; 0.42]$
5) LOS stationary	-0.06	$[-0.13; 0.01]$
6) NLOS stationary	-0.12	$[-0.18; -0.06]$

The correlation between the signal strength model errors of 2.4 and 5 GHz does not seem to be large. Hence, more information is obtained by using both frequency bands rather than only one of them. This is expected to improve the positioning.

III. POSITIONING USING WIFI SIGNALS ONLY

An important part of the positioning algorithm is the *particle filter* (PF). This is an iterative estimation method that contains various hypotheses of possible sets of states, which are called particles [4]. In our method, the states consist of the $x-$ and $y-$coordinates of the position, and the direction of movement. During each iteration, modeled RSSI values are computed for every particle, based on its current set of states. Then, these values are compared to the measured values, and each particle is assigned with a weight that corresponds to the probability of receiving the actual measurements, given its set of states. Both 2.4 and 5 GHz WiFi signals are used. Subsequently, a new set of particles is created, where those with higher weights are more likely to sustain and multiply. The last step is the state update, where the states are modified according to the modeled motion of the user.

An important part of the estimation method described above is to model the (RSSI). The model used in this algorithm is

$$\log_{10}(P_r(d)) = \log_{10}(P_r(d_0)) - 20\log_{10}\left[\frac{d}{d_0}\right] - \alpha d + X_\sigma.$$
(1)

Here, $P_r(d)$ is the received signal strength, d_0 is the reference distance of 1 meter, d is the distance between the device and the AP, and X_σ is a zero-mean Gaussian distributed random variable with standard deviation σ [5]. Further, α is a model parameter that reflects the obstacle density in the environment. Examples of obstacles in an indoor environment are walls and furniture [9]. In order to determine d between a certain particle and an AP, the position states of the particle are used.

The experiment was performed in an environment with 7 APs. A person carried the smartphone in the hand along a path of approximately 100 meters, and one set of RSSI measurements was taken each 0.5 meters. These were then used offline to reconstruct the positions using the PF, and the position error was evaluated. The initial states were treated as unknown. The experiment was performed for the following combinations of frequency bands.

1) Both 2.4 and 5 GHz.
2) 2.4 GHz only.
3) 5 GHz only.

The position error for different sets of frequencies used is presented in Table III.

TABLE II
POSITION ERROR FOR THE DIFFERENT SETS OF FREQUENCIES. USING
BOTH FREQUENCIES GAVE THE MOST ACCURATE ESTIMATES.

	Error / meter		
	1) 2.4 and 5 GHz	2) 2.4 GHz	3) 5 GHz
Mean	1.7	2.6	2.9
Maximum	4.5	5.3	5.8
Median	1.6	2.5	2.9

Using both frequency bands seems to result in the most accurate positioning, which is expected due to the low correlations between the signals in Table II.

IV. POSITIONING INCLUDING PDR

In the first part, where we compare different sets of frequency channels used, the motion of the user is modeled as a random walk. In the second part, information from the accelerometer and the gyroscope is added to the algorithm.

The accelerometer is used to detect when the user takes a step. The time derivative of the magnitude of the acceleration is determined. The sampling frequency of the accelerometer used is approximately 20 Hz, giving a frequency content of the signal between 0 and 10 Hz. However, the normal step frequency of a pedestrian is no larger than 3 Hz, which promotes filtering of the signal. Hence, a fourth order *Butterworth filter* [8] with a cut-off frequency of 3 Hz is applied. When the filtered signal passes from below to above a certain threshold level, this is used to indicate that a step has been taken. The threshold is introduced to avoid indicating steps when the user is not walking. This method is used to determine the number of steps, N, between two WiFi measurements. An example of the filtered signal together with the threshold is shown in Figure 1. The step counter has been tested while carrying the device in the hand, in a pocket and in a bag, with less than 1% error.
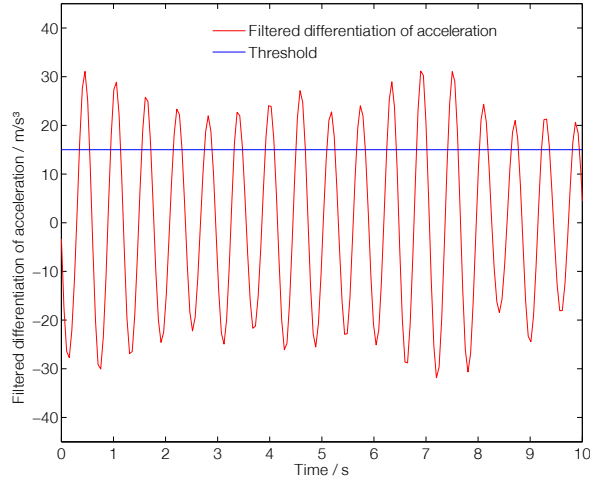
Fig. 1. Filtered accelerometer signal together with the threshold level, while walking 17 steps with the device in the hand. When the signal goes from below to above the threshold, this is used to indicate that the user has walked one step. Thanks to the differentiation and filtering of the signal, this is easy to distinguish. The threshold is introduced to avoid indicating steps when the user is not walking.

The gyroscope measures the angular velocity of the heading. This is projected on the direction of gravity, which is determined using the accelerometer. From this, the change of heading during time step k, $\Delta\theta_k$, is computed using ordinary time integration.

Using this information, the state update between time step k and $k+1$ is done as follows.

$$
\begin{aligned}
x_{k+1} &= x_k + N \cdot (l + r_k) \cdot \cos\theta_k \\
y_{k+1} &= y_k + N \cdot (l + r_k) \cdot \sin\theta_k \quad\quad (2) \\
\theta_{k+1} &= \theta_k + \Delta\theta_k + v_k
\end{aligned}
$$

Here, l is a predetermined step length. Further, r_k and v_k are Guassian random variables with zero mean and σ_r and σ_v as standard deviations.

An experiment was performed in an environment containing 20 APs. The smartphone was carried in the hand, and held reasonably fixed in relation to the user, along a path of 273 meters. The user walked in a normal walking pace, and one set of RSSI measurements was obtained every 4 seconds. Subsequently, the positions were reconstructed offline using both 2.4 and 5 GHz signals, and including the PDR.

To compare, the reconstruction was also done using the PF and WiFi only, and by using PDR only. Further, it was done using WiFi combined with the method of *least squares* (LS), which is a conventional positioning method while using signal strengths.

The initial states were treated as unknown, except while using PDR only.

The position error for the different algorithms is presented in Table III.

TABLE III

POSITION ESTIMATE ERROR USING FOUR DIFFERENT ALGORITHMS BASED ON PDR AND/OR WIFI. COMBINING WIFI AND PDR GAVE THE BEST RESULTS.

Algorithm	Maximum error / m	Average error / m
LS - WiFi Only	11.2	4.8
PF - WiFi Only	11.6	3.5
PDR only	7.7	4.2
PF - WiFi + PDR	5.8	1.3

A plot of the position estimate using WiFi combined with PDR is shown in Figure 2. A plot of the position error is shown in Figure 3.

Combining WiFi with PDR clearly provided the best positioning results. It resulted in an average error of 1.3 meters. Moreover, this method produces estimates more frequently than if only WiFi is used, since PDR estimations are performed between the WiFi measurements
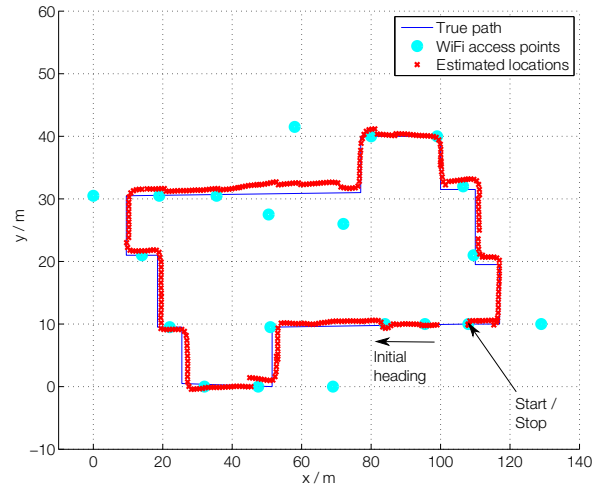

Fig. 2. Position estimate using both WiFi and pedestrian dead reckoning, along a true path of 273 meters. True start and stop point was (109;10), and the initial heading was in the negative x-direction. These were treated as unknown. The step length was considered as known and set to 0.83 meters. The average error is 1.3 meters. This proved to be the most accurate algorithm of those evaluated in this paper.

V. CONCLUSIONS

A. Using Both 2.4 and 5 GHz Signals

The correlation between the signal strength model errors of 2.4 and 5 GHz does not seem to be large (see Table II). Hence, more information is obtained by using both frequency bands rather than only one of them, which is expected to improve the positioning. This is supported by the fact that the smallest error was obtained by using signals on both frequencies, as shown in Table III.

B. Combining WiFi Measurements and PDR

Since the initial heading is treated as unknown, it is required to have more than one set of RSSI measurements
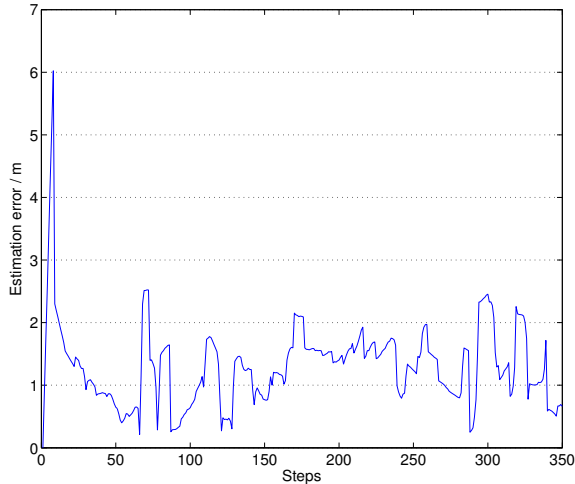
Fig. 3. Position error over the number of steps taken by the user, for the method that combines WiFi and PDR. The average error is 1.3 meters. See also Figure 2.

before the particles with consistent headings can be sorted out. Hence, the initial estimates fail to follow the movement of the user, which yields the maximum error of 5.8 meters (see Table III). This explains the gap of estimated locations in the beginning of the path in Figure 2. Once the heading is well approximated, the performance is considerably better.

This navigation system is constrained by the assumption that the localizations of the APs, and how strong the signals are transmitted, are known. The orientation of the smartphone in relation to the user is assumed to be reasonably constant. Initial heading and position are, however, assumed to be unknown. Further, the proposed algorithm will work for any kind of smartphone, as long as it is capable of receiving the WiFi signals and contains the necessary sensors. However, the representation of the RSSI varies between different models, which has to be taken into account.

Combining WiFi with PDR clearly provided the best positioning results, as shown in Table III. It resulted in an average error of 1.3 meters, along a path of 273 meters. Moreover, this method produces estimates more frequently than if only WiFi is used, since PDR estimations are performed between the WiFi measurements.

REFERENCES

[1] FARAGHER, R., AND HARLE, R, . Getting Closer to Everywhere, 2013.
[2] FISHER, R. Frequency distribution of values of the correlation coefficient in samples of an indefinitely large population. *Biometrica (Biometrica Trust) 10* (1915), 507–521.
[3] FISHER, R. On the "probable error" of a coefficient of correlation deduced from a small sample. *Metron 1* (1921), 3–32.
[4] GUSTAFSSON, F. *Statistical Sensor Fusion*. Studentlitteratur, 2012.
[5] KARLSSON, P. *Measuring and Modelling of the Indoor Radio Channel at 1700 MHz*. Sigmatryck, 1992.
[6] LI, B., SALTER, J., G., D. A., AND RIZOS, C. Indoor Positioning Techniques Based on Wireless LAN, 2007.
[7] MORRISON, A., RENAUDIN, V., BANCROFT, J. B., AND LACHAPELLE, G. Design and Testing of a Multi-Sensor Pedestrian Location and Navigation Platform, 2012.
[8] PROAKIS, J., AND MANOLAKIS, D. *Digital Signal Processing. Principles, Algorithms and Applications, 4th international edition*. Prentice Hall, 2007.
[9] RAPPAPORT, T. *Wireless Communications - Principles and Practice*. IEEE Press, 1996.
[10] RETSCHER, G., AND KEALY, A. Ubiquitous Positioning Technologies for Inteligent Navigation Systems, 2005.