LUND UNIVERSITY

Cooperative Indoor Positioning by Exchange of Bluetooth Signals and State Estimates Between Users

Karlsson, Martin; Karlsson, Fredrik

Cooperative Indoor Positioning by Exchange of Bluetooth Signals and State Estimates Between Users

Martin Karlsson[1], Fredrik Karlsson[2]

Abstract— This paper presents a Bayesian indoor positioning system for smartphones based on the strengths of WiFi and Bluetooth signals. A framework for improving the performance of existing positioning methods with the help information sharing between users is proposed and evaluated. Bluetooth signals are sent between users, and the signal strengths contain information about their relative distances, which is used to evaluate the probability distribution functions of their states. A particle filter is used for the state estimation, together with an unscented transform to propagate probability distributions through nonlinearities.

I. INTRODUCTION

The importance of generic, accurate, positioning systems is increasing, due to the numerous applications and services it enables. For most environments outdoor, the Global Positioning System (GPS) provides sufficient position estimates [1]. In urban and indoor areas, however, the GPS signals are usually too weak to provide meaningful information. Instead, several other methods, usually relying on sensor fusion of some form, have been developed. See, *e.g.*, [2], [3], [4] and [5] for some interesting examples of this, and [6] for an introductory overview of the field of indoor positioning. Previous methods range from using only one portable device, to attaching several sensors on different parts of the user's body, as in [7].

Signal strengths from closely located access points combined with pedestrian dead reckoning has also been implemented, *e.g.* as described in [8] and [9].

Meanwhile, communication between smartphones in the form of mesh networking [10] is becoming increasingly ubiquitous, usually with the purpose of increasing wireless Internet accessibility.

Also positioning with the help of Bluetooth is getting increasingly popular, but with the requirement that the environment has to be equipped with a mesh of Bluetooth beacons, which is different from the concept presented here. Examples can be found in [11], [12] and [13].

In this paper, we propose a method for promoting existing indoor positioning algorithms, where applicable. Specifically, we augment the method described in [9] in a, to the best of our knowledge, novel way, by letting the users share information about their states as well as sending Bluetooth signals to each other and measure the strengths of these. This additional information is herein shown to decrease the error of the position estimates. At the same time, no additional

[1]Department of Automatic Control, Lund University
[2]Sony Mobile Communications, Lund

requirements on the equipment and environment are implied, which is an important advantage.

II. NOTATIONS

For convenience, we here provide a list of some of the quantities used in this paper:

(x, y)	- user position coordinates
t	- time step
φ	- heading direction
$\Delta\varphi$	- change of heading direction
$P(d)$	- signal strength at distance d

These notations will be explained in more detail later on, but this list may serve as a short reference.

III. METHOD

The foundation of the positioning method is the approach described in [9]. That approach is herein extended with information exchange between different users.

A particle filter, which is well described in [14], is used to fuse the sensor data. It yields an approximation of the posterior probability distribution $p(x_t|\nu_{1:t})$, where x_t is the state at time step t, and $\nu_{1:t}$ represents the measurement data from time 1 to t. In this method, the states consist of the position coordinates, and the direction of movement. In each particle filter iteration, modeled WiFi and Bluetooth signal strengths are determined for each particle, based on its current set of states. The particle weights are then determined based on the probability of the difference between modeled and measured signal strengths. Particles with large weights, *i.e.* those with high congruity between modeled and measured measurements, have higher probability of sustaining and multiplying in the particle filter resampling step. The state update is performed each time the pedestrian dead reckoning algorithm registers that the user has taken one step, which, while walking, generally occurs more frequently than the signal strengths are obtained. Between two consecutive steps, each particle has its states modified based on the following user motion model.

$$x_{i+1} = x_i + (l + r_i) \cdot \cos\varphi_i \qquad (1)$$

$$y_{i+1} = y_i + (l + r_i) \cdot \sin\varphi_i \qquad (2)$$

$$\varphi_i = \varphi_i + \Delta\varphi_i + v_i \qquad (3)$$

Here, x and y are the position coordinates, φ is the direction of movement, l is the step length, and r_t^i and v_t^i

are zero-mean Gaussian random variables. Further, $\Delta\varphi$ is the rotation around the vertical axis as estimated by the algorithm for pedestrian dead reckoning described in [9], and i is the number of the physical step taken by the user, within time step t. In an entire particle filter iteration, the states will hence evolve according to

$$x_{t+1} = x_t + \sum_{i=1}^{n}(l + r_t^i) \cdot \cos\varphi_t^i \qquad (4)$$

$$y_{t+1} = y_t + \sum_{i=1}^{n}(l + r_t^i) \cdot \sin\varphi_t^i \qquad (5)$$

$$\varphi_{t+1} = \varphi_t + \sum_{i=1}^{n}\Delta\varphi_t^i + v_t^i, \qquad (6)$$

where n is the number of steps taken by the user within the iteration time.

In order to include the information from the WiFi access points, the measured signal strength is compared to the model

$$\log_{10}(P(d)) = \log_{10}(P(d_0)) - 20\log_{10}\left[\frac{d}{d_0}\right] - \alpha d + e, \qquad (7)$$

where $P(d)$ is the received signal strength, d_0 is the reference distance of 1 meter, d is the distance between the receiver and the transmitter, and e is zero-mean Gaussian measurement noise. More details are described in [15] and [16].

Initial experiments have shown that the Bluetooth signals behave similar to WiFi 2.4 GHz, which seems reasonable since they operate on the same frequency. The major difference is that the Bluetooth signals are transmitted with a lower intensity, and has shorter range in general. It is approximately 15 m, but very dependent on the environment. Furthermore, the model of signal strengths between two users is slightly more involved than that of a signal from an access point, due to the uncertainty of the position of a transmitting user. In addition to the noise e, the position (x_{tr}, y_{tr}) of the transmitting user will in this case be a random variable with a certain mean and variance, which will have to be propagated through the nonlinear function (7) in order to compute the probabilities of the particles. (The time dependency has been omitted to keep the notation uncluttered.) This is achieved by using the unscented transform [17], according to which sample points χ and corresponding weights w should be chosen from the probability distribution of (x_{tr}, y_{tr}). These are chosen according to

$$\begin{aligned}
\chi_0 &= \mu, & \omega_0 &= \frac{\kappa}{n+\kappa} \\
\chi_j &= \mu + (\sqrt{(n+\kappa)\Sigma})_j, & \omega_j &= \frac{1}{2(n+\kappa)} \\
\chi_{n+j} &= \mu - (\sqrt{(n+\kappa)\Sigma})_j, & \omega_{n+j} &= \frac{1}{2(n+\kappa)}
\end{aligned}$$

where n is the dimension of the input probability distribution, $j = 1, 2...n$, κ is a tuning parameter, M_j denotes column j of the matrix M, μ denotes the mean and Σ the covariance matrix of the probability distribution. These

points are to be propagated through the nonlinearity (7), and then the corresponding weighted mean and variance of the modeled Bluetooth signal strength at the receiving user are determined. Finally, these values are used to weight the particles of the receiving user. This procedure should be done in both ways, for all users that are in range of each other.

IV. SIMULATIONS

In order to evaluate the method, simulations were performed in the Julia programming language [18]. The environment resembles an open office building called Glasgow, situated in Lund, Sweden. An example floor plan is shown in Figure 6. Please note, however, that these differ for different floors. Glasgow has 20 WiFi access points on each floor, and in the simulations, they are positioned according to the arrangement on the top floor. Further, walls and furniture are assumed to be unknown in the models, in order to preserve generality.

Two different situations were considered. Firstly, a group of 10 users move together as a group through the floor (see Figure 1). Secondly, 100 users perform uncorrelated random walks (see Figure 4). The cases are described in more detail in the following subsections.

A. Users as a group

Initially, the users were spread randomly around point $(x, y) = (20, 5)$ m. Then, they moved in the approximate direction of (-1,1), followed by a right turn, and finally they moved across the floor in the approximate direction of (1,0). The reason for the directions being approximate is that the movement contained a random part as well as a deterministic one.

For the state estimation, the users were assumed to use pedestrian dead reckoning combined with measurements from WiFi and Bluetooth. The results are shown in Figure 1, 2 and 3, as well as in Table I.

This was then compared to the same case, with all parameters kept the same, but where only pedestrian dead reckoning and WiFi were used. This is the method described in [9]. This resulted in significantly larger positioning errors, as shown in Figure 3 and Table I.

TABLE I

AVERAGE AND MAXIMUM POSITION ERROR, TAKEN OVER ALL USERS AND ALL TIME STEPS, FROM THE SIMULATION OF 10 USERS WALKING AS A GROUP. SEE ALSO FIGURE 3, WHERE THE AVERAGE USER ERROR IS PLOTTED AGAINST TIME STEP.

Method	Average error	Maximum error
Bluetooth not included	1.0249 m	3.9435 m
Bluetooth included	0.7388 m	2.5618 m

B. Uncorrelated random walks

Many situations can be thought of where pedestrian dead reckoning data are not available, *e.g* due to absence of gyroscope or accelerometer, or when something other than a pedestrian should be positioned. In order to take this into account, simulations were performed where no information
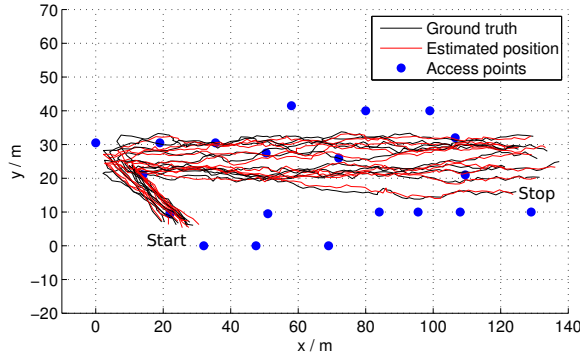
Fig. 1. The ground truth and estimated positions of 10 users walking in a group from the region marked 'Start' to the one marked 'Stop'. Due to the randomness in the generation of the true trajectory, the users diverge slightly from each other. Both pedestrian dead reckoning, WiFi and Bluetooth were used for the state estimation shown in this plot. See also Figure 2, where the data of one user was selected and displayed for a clearer view.
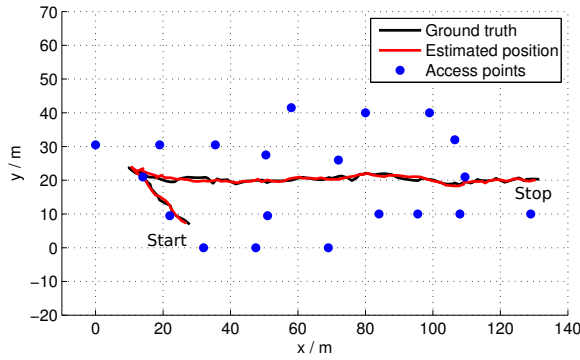

Fig. 2. This plot is similar to Figure 1, but with data from only one of the users shown, in order to get a less cluttered version.
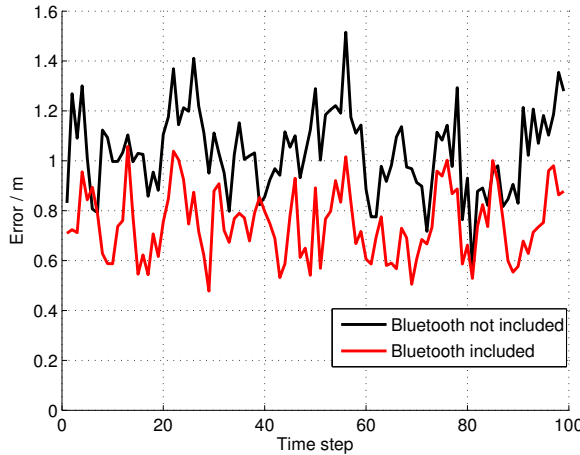

Fig. 3. The position error averaged over all users, plotted against the time steps, from the simulation of 10 users walking as a group. Note that since the errors are averaged, the maximum values seen here are much lower than those shown in Table I. The average error values, however, correspond.

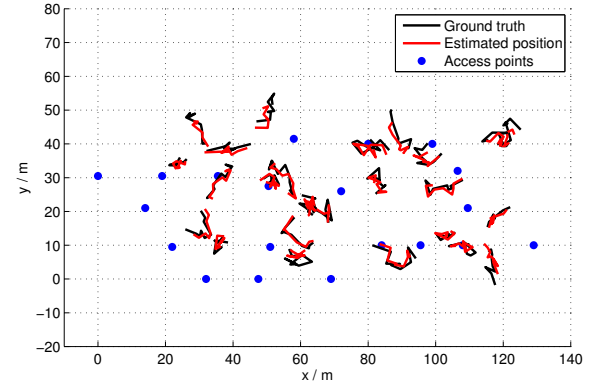about direction was assumed. Instead, the movement was

Fig. 4. The ground truth and estimated positions from the simulation with uncorrelated random walks. The simulation covered 100 users, but in order to keep the image clearer, only the data from 25 of these are shown herein. Note that due to the limited signal range, a certain user will receive signals only from close peer users and access points.

modeled as a random walk, according to

$$x_{t+1} = x_t + \delta x_t \tag{8}$$
$$y_{t+1} = y_t + \delta y_t \tag{9}$$

where δx_t and δy_t are Gaussian random variables with zero-mean and a standard deviation of 2 m. In this scenario, 100 users were initially spread randomly across the area. Then, each user performed a random walk, independently, for 10 time steps. The movement is shown in Figure 4. This time, the positioning was carried out using both WiFi and Bluetooth, and for comparison, it was also done with WiFi only. The results are shown in Figure 4 and 5, as well as Table II. Also in this setup, the cooperative behavior decreases the error significantly.

TABLE II

AVERAGE AND MAXIMUM POSITION ERROR, TAKEN OVER ALL USERS AND ALL TIME STEPS, FROM THE SIMULATION OF 100 USERS WALKING RANDOMLY. SEE ALSO FIGURE 5, WHERE THE AVERAGE USER ERROR IS PLOTTED AGAINST TIME STEP.

Method	Average error	Maximum error
Bluetooth not included	1.7288 m	7.7817 m
Bluetooth included	1.3357 m	6.6836 m

V. DISCUSSION

The proposed method increases the positioning performance for the scenarios addressed here, which seems reasonable since more information is included. It should, however, be stated that far from all possible indoor positioning scenarios have been investigated, and real-world experiments remain as future work (see Section VII). Nevertheless, the work presented here should serve as a proof of concept, and hopefully as an idea to build on.

Both the simulation of the ground truth data and the estimation methods are stochastic, and hence the results vary slightly from one simulation to another. However, the
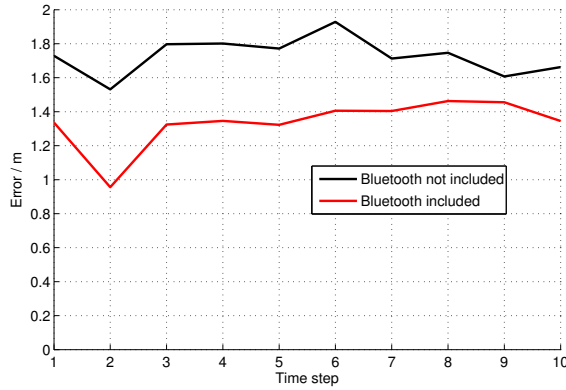
Fig. 5. The position error averaged over all users, plotted against the time steps, from the simulation of 100 users walking randomly. Note that since the errors are averaged, the maximum values seen here are much lower than those shown in Table II. The average error values, however, correspond.
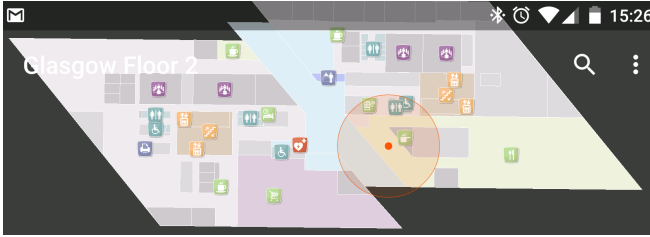

Fig. 6. A map of one of the floors in the Glasgow building, situated in Lund, Sweden, as displayed in the smartphone indoor positioning application SonyMap [19]. The simulations in this paper are based on this environment. The state estimation in SonyMap is implemented as described in [9], and it remains as future work to augment the application according to the method described here.

simulations were repeated several times to verify that the results presented here are representative.

The WiFi signals from access points and Bluetooth signals from peer users are treated in similar manners, but WiFi signals provide more accurate information, since the access points are assumed to be known, while the states of the peer users are described by approximate probability distributions. This is taken into account by the unscented transform. However, the same principle can be used when the positions of WiFi access points are uncertain, for example as a result of mapping by crowd sourcing, or simultaneous mapping and localization (SLAM). One should then, however, take into account that it is known that the access points do not move, as oppose to the users.

In order to perform the sensor fusion, there are several alternatives to the particle filter and the unscented transform used here. One could, for instance, use an extended Kalman filter instead of the particle filter. Both of these estimations can handle nonlinear systems, but the particle filter has the advantage of being able to approximate any probability density function in the state space, which is why it was chosen. Further, a cubature transform [20] could be used instead of the unscented transform.

One could also consider to linearize Equation (7). This would be computationally cheaper, but slightly less accurate.

During the work presented here and in [9], attempts were made to model the user step length as another state to be estimated. This came with the price of increased computational cost, without any significant improvement of the accuracy.

VI. CONCLUSIONS

In this paper, we have presented a method for indoor positioning. The main contribution is the framework for sending Bluetooth signals, as well as data about the states, between users, in order to get more information for the sensor fusion algorithm. Simulations have been run to evaluate the method, both for the case where pedestrian dead reckoning has been available, and where it has not. WiFi signals from known access points have served as a foundation for both cases considered. It is demonstrated that the cooperative behavior described here promotes the performance of the state estimation significantly, which forms a win-win relationship between the users.

VII. FUTURE WORK

As a next step in this work, real-world data should be acquired. Smartphones should be used to

- Receive WiFi signals
- Receive and transmit Bluetooth signals
- Log gyroscope and accelerometer

while the ground truth positions are observed externally for evaluation of the method. The data should then be used to reconstruct the user trajectories offline.

Subsequently, the state estimation in the smartphone application SonyMap (see [19] and Figure 6) should be augmented to include Bluetooth signals between users. Currently, the application performs one particle filter iteration every few seconds, whereas the computation run time is much shorter. Further, including the Bluetooth signals does not imply enough additional computational cost for this to be critical. Hence, this seems to be a computationally feasible ambition.

It is expected that the performance is dependent on the number of users involved. For the extreme case of one user only, the algorithm is equivalent to the case where only WiFi is used. No significant improvement could be seen in the simulations for trials with less than five users. However, it remains as future work to investigate the relation between performance and number of users more thoroughly.

ACKNOWLEDGMENTS

REFERENCES

[1] J. G. Grimes, "Global positioning system standard positioning service performance standard, 4th edition," Department of Defense, United States of America, Tech. Rep., 2008.

[2] L. Li, G. Shen, C. Zhao, T. Moscibroda, J.-H. Lin, and F. Zhao, "Experiencing and handling the diversity in data density and environmental locality in an indoor positioning service," in *Proceedings of the 20th annual international conference on Mobile computing and networking.* ACM, 2014, pp. 459–470.

[3] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *Mobile Computing, IEEE Transactions on*, vol. 11, no. 12, pp. 1983–1993, 2012.

[4] T. Gallagher, E. Wise, B. Li, A. G. Dempster, C. Rizos, and E. Ramsey-Stewart, "Indoor positioning system based on sensor fusion for the blind and visually impaired," in *Indoor Positioning and Indoor Navigation (IPIN), 2012 International Conference on.* IEEE, 2012, pp. 1–9.

[5] B.-S. Choi, J.-W. Lee, J.-J. Lee, and K.-T. Park, "A hierarchical algorithm for indoor mobile robot localization using rfid sensor fusion," *Industrial Electronics, IEEE Transactions on*, vol. 58, no. 6, pp. 2226–2235, 2011.

[6] R. Mautz, "Indoor positioning technologies," 2012, Institute of Geodesy and Photogrammetry, Department of Civil, Environmental and Geomatic Engineering, ETH Zurich.

[7] A. Morrison, V. Renaudin, J. B. Bancroft, and G. Lachapelle, "Design and Testing of a Multi-Sensor Pedestrian Location and Navigation Platform," 2012.

[8] M. Luna, G. Meifeng, Z. Xinxi, Z. Yongjian, and S. Mingliang, "An indoor pedestrian positioning system based on inertial measurement unit and wireless local area network," in *Control Conference (CCC), 2015 34th Chinese.* IEEE, 2015, pp. 5419–5424.

[9] F. Karlsson and M. Karlsson, "Sensor fused indoor positioning using dual band wifi signal measurements," in *European Control Conference (ECC), 2015 34th.* IEEE, 2015.

[10] S. Vural, D. Wei, and K. Moessner, "Survey of experimental evaluation studies for wireless mesh network deployments in urban areas towards ubiquitous internet," *Communications Surveys & Tutorials, IEEE*, vol. 15, no. 1, pp. 223–239, 2013.

[11] L. Chen, L. Pei, H. Kuusniemi, Y. Chen, T. Kröger, and R. Chen, "Bayesian fusion for indoor positioning using bluetooth fingerprints," *Wireless personal communications*, vol. 70, no. 4, pp. 1735–1745, 2013.

[12] F. Subhan, H. Hasbullah, A. Rozyyev, and S. T. Bakhsh, "Indoor positioning in bluetooth networks using fingerprinting and lateration approach," in *Information Science and Applications (ICISA), 2011 International Conference on.* IEEE, 2011, pp. 1–9.

[13] A. Baniukevic, C. S. Jensen, and H. Lu, "Hybrid indoor positioning with wi-fi and bluetooth: architecture and performance," in *Mobile Data Management (MDM), 2013 IEEE 14th International Conference on*, vol. 1. IEEE, 2013, pp. 207–216.

[14] F. Gustafsson, "Particle filter theory and practice with positioning applications," *Aerospace and Electronic Systems Magazine, IEEE*, vol. 25, no. 7, pp. 53–82, 2010.

[15] P. Karlsson, *Measuring and Modelling of the Indoor Radio Channel at 1700 MHz.* Sigmatryck, 1992.

[16] T. Rappaport, *Wireless Communications - Principles and Practice.* IEEE Press, 1996.

[17] E. Wan, R. Van Der Merwe, *et al.*, "The unscented kalman filter for nonlinear estimation," in *Adaptive Systems for Signal Processing, Communications, and Control Symposium 2000. AS-SPCC. The IEEE 2000.* IEEE, 2000, pp. 153–158.

[18] J. Bezanson, A. Edelman, S. Karpinski, and V. B. Shah, "Julia: A fresh approach to numerical computing," November 2014.

[19] Sony Mobile Communications. (2015) SonyMap. [Online]. Available: https://http://developer.sonymobile.com/knowledge-base/technologies/indoor-maps/

[20] B. Jia, M. Xin, and Y. Cheng, "High-degree cubature kalman filter," *Automatica*, vol. 49, no. 2, pp. 510–518, 2013.