Enhancement of Localization Accuracy in Cellular Networks via Cooperative AdHoc Links

Lhomme, Edouard; Frattasi, Simone; Figueiras, Joao; Schwefel, Hans-Peter

Published in:
Proceedings of the 3rd IEE Mobility Conference

Publication date:
2006

Document Version
Publisher's PDF, also known as Version of record

Enhancement of Localization Accuracy in Cellular Networks via Cooperative Ad-Hoc Links

Edouard Lhomme
edouard.lhomme@gmail.com

Simone Frattasi
sf@kom.aau.dk

João Figueiras
jf@kom.aau.dk

Hans-Peter Schwefel
hps@kom.aau.dk

Center for TeleInFrastruktur (CTIF), Aalborg University
Niels Jernes Vej 12, 9220, Aalborg, Denmark

ABSTRACT

Positioning information enables new applications for cellular phones, personal communication systems, and specialized mobile radios. The *network heterogeneity* emerging in the fourth generation (4G) of mobile networks can be utilized for enhancements of the location estimation accuracy. In this paper, we propose a method to perform the localization in a system based on the coexistence of the *cellular* and the *ad-hoc* links. The main contribution of this paper is the implementation and evaluation of an Extended Kalman Filter, which merges two available domains of measurements: the time difference of arrival and the received signal strength, respectively retrieved from the long- and the short-range segments. The simulation results show that the proposed localization system outperforms a stand-alone cellular system in the considered scenarios.

Keywords

cooperative localization, cellular networks, ad-hoc networks, Extended Kalman Filter, time difference of arrival, received signal strength.

1. INTRODUCTION

The increasing popularity of mobile technologies opens up a new market of useful additional services, like location assistance, tracking, and localized data downloading. The mandate for providing location information on mobiles started when the National Association of State Nine-One-One Administrator (NASNA), the National Emergency Number Association (NENA), the Public-Safety Communications Officials (APCO) and the Cellular Telecommunications Industry (CTIA) encouraged the Federal Communications Commission (FCC) to adopt some regulations to improve the quality of emergency services: in 1994, the FCC required the American operators to provide positioning information for emergency calls with an accuracy of 125 m in 67% of the cases [1]. These regulations had hence affected the existing second generation (2G) of mobile communication systems (which was not originally designed to provide such information), and created even higher expectations fur subsequent network evolution steps.

The use of the Global Positioning System (GPS) for location of mobiles has been applied in the third generation (3G). However, the introduction of mobile handsets with built-in GPS receivers leads to an increased cost, size, battery consumption, and a long time for a full market penetration. Furthermore, the location estimation accuracy obtained by the GPS degrades in urban and indoor environments, which actually represent the greatest interest of cellular network providers and service providers in general [2]. Hence, investigations started in connection with the fourth generation (4G), where the new systems will take advantage of the emerging *network heterogeneity* [3]. The need is to define a polyvalent solution based on different communication technologies, which is also able to provide location information with a high level of accuracy *anywhere* and *anytime*.

In this paper, we propose a method to perform the localization service in a system based on the coexistence of the *cellular* and the *ad-hoc* network models. Each mobile station (MS) is thus assumed to receive signals for locatlization purposes both from the base stations (BSs)and from neighbouring MSs. As a reference system, we consider a Wireless Wide Area Network (WWAN) / Wireless Local Area Network (WLAN) system, such as the Universal Mobile Telecommunications System (UMTS) and the WLAN 802.11a, which integrates respectively two types of wireless access technologies: the Wideband Code Division Multiple Access (WCDMA) and the Orthogonal Frequency Division Multiplexing (OFDM). The positioning techniques employed in such a system are chosen to be the time difference of arrival (TDOA) and the received signal strength (RSS), respectively for the long- and short-range segments. Each MS retrieves and forwards its own set of time-difference and range-based estimations to the cellular network, which is then in charge of calculating the location estimates for all the *cooperative* mobiles. The main contribution of this paper is the implementation and evaluation of an Extended Kalman Filter (EKF), which merges the two available domains of measurements.

The rest of the paper is organized as follows: Section 2 presents the related work on positioning in cellular and ad-hoc networks; Section 3 describes the overall architecture of the proposed localization system; and Section 4 discusses its performance evaluated via simulations. Finally, the concluding remarks are given in Section 5.

2. RELATED WORK

2.1 Cellular & Ad-Hoc Positioning Techniques

Wireless localization techniques fall into two main categories: *mobile-based* and *network-based*. In mobile-based localization, the MS determines its location from signals received from some fixed reference points, e.g., BSs, or from the GPS. Network-based location, instead, relies on some existing networks, e.g., cellular networks, to determine the position of a mobile user by measuring its signal parameters when received at the network BSs; these measures are then relayed to a central site for further processing and data fusion to provide an estimate of the MS's location. Both categories of location technologies can involve the measurements of the time of arrival (TOA), the TDOA, and the RSS of radio signals either received or transmitted by the MS. Although received signal strength measurements are easily available, the RSS technique has been circumvented in cellular networks because its accuracy depends strongly on the distance of the located device from the BSs. Hence, the dominant location techniques in WWANs are TOA and TDOA. Whereas in TOA location a tight synchronization between the clocks of the transmitting BS and the receiving MS is needed, in TDOA location the accuracy is a function of the relative BS geometric positions [4]. The dominant location techniques in ad-hoc networks, e.g., WLANs, are TOA and RSS [5]. Whereas TOA measurements are preferred for sparse networks, for sufficiently high density ones, since the distances are sensibly reduced and hence the likehood to have a fixed reference point close to the located device is substantial, RSS can perform as well as TOA [6].

2.2 The Extended Kalman Filter

One of the most famous techniques to enhance accuracy of positioning systems is the use of statistical filtering methods. From the different filters available in literature [7], we have chosen the Kalman filter (KF) [8], due to its implementation simplicity and, at the same time, its high performance in many different scenarios. Basically, the KF predicts the consecutive "hidden" states of a determined system, based on measurements of "visible" quantities that can be related with those states. However, the KF can only be applied on linear systems. As a consequence, a later development of the KF, namely the EKF [8], was done in order to consider non-linear systems. In short, the EKF linearizes the non-linearities in the points dictated by the current states. It is basically a cyclic estimator, where states are predicted/propagated in time and then corrected every time a new measurement is obtained. To implement the filter, it is necessary to define two models: the evolution model (in localization terms commonly called motion model), which relates the previous state with the new one; and the perceptual model, which relates the measurements with the states. Assuming that our state is the vector x_k and our measurement is the vector z_k, we define the evolution and perception models as:

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \tag{1}$$

$$z_k = h(x_k, v_k) \tag{2}$$

where k represents the discrete time, u_k represents an external excitation of the system, and w_k and v_k the process and measurements noise, respectively. The variables w_k and v_k must be independent and follow a Gaussian distribution with covariances Q and R, respectively. Having defined the dependencies in Eq. (1) and Eq. (2), the filter is defined as:

Prediction:

$$\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0) \tag{3}$$

$$P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \tag{4}$$

Correction:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + V_k R_k V_k^T)^{-1} \tag{5}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-, 0)) \tag{6}$$

$$P_k = (I - K_k H_k) P_k^- \tag{7}$$

where:

$\hat{x}_k$	–	Estimation of x_k at time k
$\hat{x}_k^-$	–	Prediction of x_k at time k
P_k	–	Estimation of the covariance error at time k
P_k^-	–	Prediction of the covariance error at time k
A_k	–	Jacobian of Eq. (1) in order to x_k
W_k	–	Jacobian of Eq. (1) in order to w_k
H_k	–	Jacobian of Eq. (2) in order to x_k
V_k	–	Jacobian of Eq. (2) in order to v_k.

For the first estimation at time $k = 0$, a value for $\hat{x}_0$ and P_0 needs to be guessed. A simple solution is to adopt $\hat{x}_0$ as one of the probable states and $P_0 = Q$.

3. SYSTEM ARCHITECTURE

3.1 Scenario Description

As shown in Fig. 1, we consider a scenario where four BSs run the necessary procedures to localize two MSs. The communication between these BSs and the MSs is based on WCDMA, while the communication between the MSs is based on OFDM. Micro cells of 2000 m of diameter have been considered, where a hexagonal test cell is surrounded by the remaining three neighbouring cells. The four BSs and two MSs are placed in a two-dimensional (2D) plane with coordinates $BS_1(x_a, y_a)$, being the home BS (reference BS for the TDOA measurements), $BS_2(x_b, y_b)$, $BS_3(x_c, y_c)$, and $BS_4(x_d, y_d)$, and $MS_1(x_1, y_1)$ and $MS_2(x_2, y_2)$, respectively. For simplification, the position of each MS is assumed to be static, therefore during the number of iterations considered for the location estimation, there is no relative movement between each MS and the BSs, and between the MSs themselves. From the propagation point of view, the long- and short-range measurements are assumed to be made under line of sight (LoS) conditions.

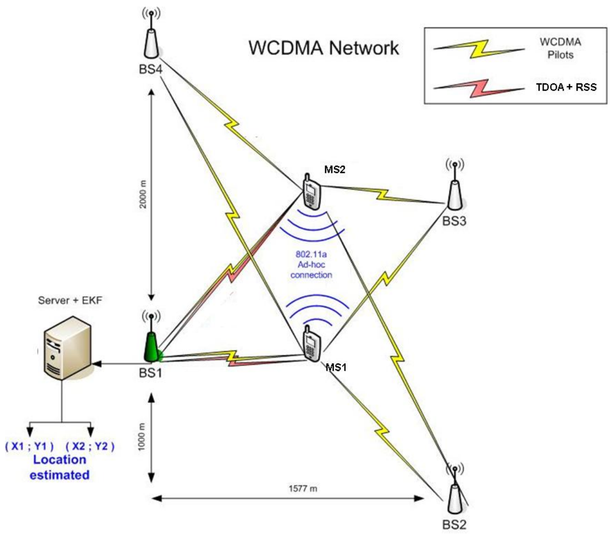

Figure 1: Reference scenario.

3.2 Proposed Localization System

The procedure implemented to obtain the localization service in the proposed system is shown in Fig. 2 and explained in the following:

1. Each MS sends a positioning request to the cellular network, which initializes the enhanced localization process;

2. Each MS measures (a) the time arrival difference between the pilot signals of a neighbouring BS and the home BS by cross-correlating them; and (b) the received signal strength of the pilot signals generated by the other MS;

3. Each MS transmits the set of TDOA and RSS measurements to the home BS, which forwards this information to a location server;

4. The location of both MS_1 and MS_2 is calculated by using the EKF algorithm (see Section 2.2) with the set up shown in Section 3.3.

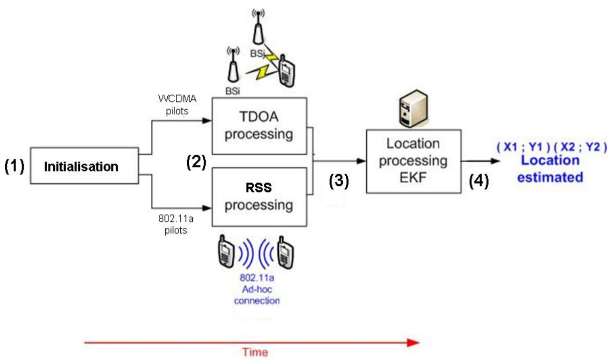

Figure 2: Localization procedure.

3.3 Filter Modelling

3.3.1 States and Measurements

In order to model the EKF filter, we first define the state space and the measurement space:

$$\hat{x}_k = [\hat{x}_{1,k}, \hat{y}_{1,k}, \hat{x}_{2,k}, \hat{y}_{2,k}]^T \tag{8}$$

$$z_k = [T_{112}, T_{113}, T_{114}, T_{212}, T_{213}, T_{214}, P_{12}, P_{21}]^T \tag{9}$$

As we can see in Eq. (8), our state is formed by the position estimators $(\hat{x}_{m,k}, \hat{y}_{m,k})$ ($m = 1$ for MS_1 and $m = 2$ for MS_2) of both mobiles. In Eq. (9), the measurements are the values of TDOA T_{mno} (m=1 for MS_1 and $m = 2$ for MS_2; while values of time differences between BS o and n are obtained) and values of signal strength attenuation P_{ij} (when mobile i measures the received power sent by mobile j).

3.3.2 Motion and Perception Models

By assuming that the mobiles are static, we imply that there is no motion model and, consequently, that the new state $\hat{x}_k^-$ in Eq. (1) is equal to the previous state $\hat{x}_{k-1}^-$:

$$\hat{x}_k^- = \hat{x}_{k-1}^- \tag{10}$$

Concerning the perception model, we have two different domains of measurements, i.e., TDOA and RSS estimates, which are modeled by using the hyperbola and the free space path loss equation respectively:

$$\begin{aligned} T_{mno} &= h_1(\hat{x}_{m,k}; \hat{y}_{m,k}; x_n; y_n; x_o; y_o) \\ &= \frac{1}{c}\Bigg[\sqrt{(\hat{x}_{m,k} - x_o)^2 + (\hat{y}_{m,k} - y_o)^2} \\ &- \sqrt{(\hat{x}_{m,k} - x_n)^2 + (\hat{y}_{m,k} - y_n)^2}\Bigg] \end{aligned} \tag{11}$$

$$\begin{aligned} P_{m_1 m_2} &= h_2(\hat{x}_{m_1,k}; \hat{y}_{m_1,k}; \hat{x}_{m_2,k}; \hat{y}_{m_2,k}) \\ &= -27.56 + 20\, log_{10}(f) \\ &+ 10\, log_{10}\Big[(\hat{x}_{m_1,k} - \hat{x}_{m_2,k})^2 + (\hat{y}_{m_1,k} - \hat{y}_{m_2,k})^2\Big] \end{aligned} \tag{12}$$

Eq. (2) becomes:

$$h = \begin{bmatrix} h_1(\hat{x}_{1,k}; \hat{y}_{1,k}; x_a; y_a; x_b; y_b) \\ h_1(\hat{x}_{1,k}; \hat{y}_{1,k}; x_a; y_a; x_c; y_c) \\ h_1(\hat{x}_{1,k}; \hat{y}_{1,k}; x_a; y_a; x_d; y_d) \\ h_1(\hat{x}_{2,k}; \hat{y}_{1,k}; x_a; y_a; x_b; y_b) \\ h_1(\hat{x}_{2,k}; \hat{y}_{1,k}; x_a; y_a; x_c; y_c) \\ h_1(\hat{x}_{2,k}; \hat{y}_{1,k}; x_a; y_a; x_d; y_d) \\ h_2(\hat{x}_{1,k}; \hat{y}_{1,k}; \hat{x}_{2,k}; \hat{y}_{2,k}) \\ h_2(\hat{x}_{2,k}; \hat{y}_{2,k}; \hat{x}_{1,k}; \hat{y}_{1,k}) \end{bmatrix} \tag{13}$$

where:

(x_n, y_n)	–	Location of the reference BS
(x_o, y_o)	–	Location of the remaining BSs ($o \neq n$)
c	–	Speed of light (m/s)
f	–	Operating frequency (Hz).

3.3.3 Process and Measurement Noise

By assuming that the mobiles are static, we imply that no process noise exists and subsequently Q would be equal to the null matrix. However, in order to allow a faster convergence of the filter, we consider Q as a diagonal matrix with variance values some order smaller than the expected values of the states:

$$Q = \sigma_{xy}^2 I(4) \tag{14}$$

with $\sigma_{xy} \sim 10^{-5}m$ (from now on, the notation $I(i)$ represents the identity matrix of dimension $i \times i$). Concerning the measurement noise, we consider R as a diagonal matrix (no correlation between measurements), where the variances σ_{TDOA}^2 and σ_{RSS}^2 are obtained from simulation data:

$$R = \left[\begin{array}{c|c} \sigma_{TDOA}^2 I(6) & 0 \\ \hline 0 & \sigma_{RSS}^2 I(2) \end{array} \right] \tag{15}$$

3.3.4 Filter Parameters

In order to model our filter, it is still missing to define the matrices in Eq. (4) and Eq. (5). Assuming, for simplification, that our system only includes additive Gaussian noise, the matrices W_k and V_k are equal to the identity matrix, independently from the time k. The matrices A_k and H_k represent the Jacobian of Eq. (10) and Eq. (13), respectively. Since the mobiles are static, A_k is equal to the identity matrix. Taking this fact into consideration, Eq. (4) and Eq. (5) turn into:

$$P_k^- = P_{k-1} + Q \tag{16}$$

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R)^{-1} \tag{17}$$

4. SIMULATION RESULTS

System level simulations have been performed in order to compare the location estimation accuracy of the proposed localization system and a stand-alone WCDMA cellular system. To give a comparison between them, the localization error is calculated by varying the position of the MSs on a straight line joining the barycenter of the two MSs to the home BS. The parameters used in the simulations are listed in the following table:

Table 1: Simulation parameters.

PARAMETERS	VALUES
Cell radius	1000 m
Number of BSs	4
Number of MSs	2
Distance MS_1-MS_2	30 m
Measurements per BS	1000
Measurements per MS	1000

From the results illustrated in Fig. 3, it is observed that: 1) Regardless the location of the MSs, the proposed localization system always performs better than a stand-alone WCDMA cellular system. Indeed, with the specific simulation models taken into consideration, the range of localization errors for a WCDMA system is between 60 m and 120 m, whereas for the proposed localization system, the localization error is between 17 m and 90 m; 2) When the MSs are relatively close to the home BS, the localization errors become smaller, thus achieving an accuracy very much comparable to the GPS [9]; and 3) The localization errors between our proposal and the pure cellular solution tend to converge when the distance increases from the home BS and the MSs get closer to the cell boundary.

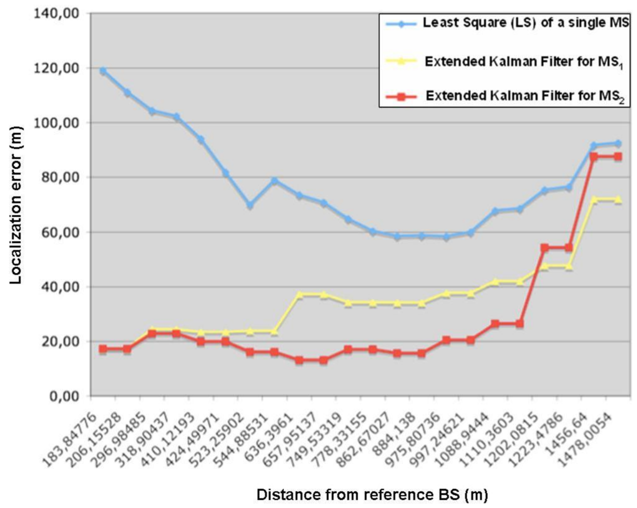

Figure 3: Localization error vs. distance of the MSs from the home BS.

5. CONCLUSIONS

In this paper, we have presented a new concept for cellular localization, which makes use of the additional information coming from ad-hoc links to enhance the location estimation accuracy of the mobiles in a cell. We have hence developed a data fusion method based on the EKF, where the RSS measurements are merged with the TDOA measurements. The proposed localization system, when compared with a stand-alone WCDMA cellular system, has proven to enhance the location estimation accuracy in cellular networks. As future work, we mainly intend to consider mobility and scalability issues.

6. REFERENCES

[1] FCC. FCC Acts to Promote Competition and Public Safety in Enhanced Wireless 911 Services. *Washington, DC: WT Rep. 99-27*, September 1999.

[2] A. H. Sayed, A. Tarighat, and N. Khajehnouri. Network-Based Wireless Location: Challenges Faced in Developing Techniques for Accurate Wireless Location Information. *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 24-40, July 2005.

[3] S. Frattasi, H. Fathi, F. H. P. Fitzek, M. Katz, and R. Prasad. Defining 4G Technology from the User Perspective. *IEEE Network Magazine*, vol. 20, no. 1, pp. 35-41, January-February 2006.

[4] Zhao Y. Mobile Phone Location Determination and Its Impact on Intelligent Transportation Systems. *IEEE Trans. on Intelligent Transportation Systems*, vol. 1, no. 1, pp. 55-64, March 2000.

[5] H. P. Schwefel, J. Figueiras, and I. Z. Kovacs. Accuracy and Timing Aspects of Location Information Based on Signal-Strength Measurements in Bluetooth. In *Proc. of IEEE International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, vol. 4, pp. 2685-2690, Berlin, Germany, September 2005.

[6] N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero, R. L. Moses, and N. S. Correal. Locating the Nodes: Cooperative Localization in Wireless Sensor Networks. *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54-69, July 2005.

[7] D. Fox, J. Hightower, L. Liao, D. Schulz, and G. Borriello. Bayesian Filtering for Location Estimation. *IEEE Pervasive Computing*, vol. 2, no. 3, pp. 24-33, July-September 2003.

[8] M. S. Grewal, and A. P. Andrews. Kalman Filtering: Theory and Practice Using MATLAB. *Wiley*, 2nd Edition, 2001.

[9] Assistant Secretary of Defence for Command, Control, Communications, and Intelligence. Global Positioning System — Standard Positioning Service — Performance Standard. October 2001.