Experimental Activity on Cooperative Mobile Positioning in Indoor Environments

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Abstract

Traditional localization systems are based on the information obtained from some fixed reference points (e.g., Access Points (APs)) to Mobile Station (MS) links; typically for short-range, Received Signal Strength Difference (RSSD) or Received Signal Strength (RSS) measurements are used. In order to enhance the accuracy of localization systems indoors, the innovative solution presented in this paper considers also the information obtained from MS-MS links. A proof of concept in a real scenario is implemented in an indoor environment by using a Wireless Local Area Network (WLAN), and the results show that the accuracy is enhanced with respect to non-cooperative schemes. Non-Linear Least Square (NLLS) and Extended Kalman Filter (EKF) are used as data fusion algorithms to combine RSSD measurements from AP-MS links and RSS measurements from MS-MS links.

Index Terms—Cooperation, Localization, Data Fusion, Extended Kalman Filter (EKF), Non-Linear Least Square (NLLS).

1. INTRODUCTION

Nowadays, localization in wireless technology represents a great interest and a major importance for society and industry. Indeed, it can be used in many applications such as emergency, security, tracking, monitoring, intelligent transportation systems, mobile yellow pages, and cellular system management [1].

Traditional positioning methods can be classified into three main categories [2]: network-based, where a Fixed Reference Point (FRP) in the network performs both positioning measurements and computations for obtaining a location estimate of the Mobile Station (MS); mobile-based, where the MS performs both positioning measurements and computations for obtaining its location estimate; and mobile-assisted, where the MS provides positioning measurements to the network for computations of its location estimate. In this paper, the mobile-assisted method will be adopted. Furthermore, there are four different positioning techniques that are commonly used, namely [2]:

- Angle Of Arrival (AOA): It utilizes multi-array antennas and tries to estimate the line of arrival of the signal. The position of the MS can be located at the intersection of the lines if more than one AOA measurements is performed. Note that AOA requires Line of Sight (LOS) to achieve better accuracy.
- Time Of Arrival (TOA): TOA information from the MS to the FRP or vice versa can be estimated if both entities are precisely synchronized in time. To estimate the position of the MS, at least three different FRPs are required for multilateration.
- Time Difference Of Arrival (TDOA): It is based on estimating the difference in the arrival times of the signals coming from two different transmitters at the receiver by cross-correlation. The peak of the cross-correlation output gives the TDOA estimation. Geometrically a particular TDOA value defines an hyperbola between the two receivers on which the MS may be located. The position of the MS can be estimated at the intersection of the hyperbola if more than one TDOA measurements is performed. One of the benefits of this technique is that it does not require knowledge of the absolute time of the transmission.
- Received Signal Strength Difference (RSSD): It can be used to estimate the position of the MS in a short-range system. Specifically, RSSD measurements result from received-power-difference at the MS from couples of APs. As for TDOA, geometrically a particular RSSD value defines an hyperbola between the two receivers on which the MS may be located. Note that TDOA estimations cannot be usually used in short-range, since a small error in time-difference is translated in a high distance-error when compared to the real short-range distances in the network.

When localization is performed in cellular networks (mostly outdoors), the accuracy is highly dependent on the wireless channel conditions. This becomes even more evident indoors, as the intrinsical complexity of the environment makes shadowing and multipath cause high fluctuations in received power, which introduce high localization errors. In this paper, we propose an innovative solution to increase the localization accuracy in indoor

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scenarios. Basically, this is achieved by allowing cooperation between MSs and exploiting their ad-hoc communications to combine RSSD measurements from AP-MS links and RSS measurements from MS-MS links. In particular, our aim is to proof the concept of cooperation and demonstrate it in a WLAN 802.11b network.

The paper is organized as follows: Section 2 describes the experiment, which includes scenario, communication protocol, calibration, data fusion, results and analysis. Finally, our concluding remarks are given in Section 3.

2 EXPERIMENT

2.1 Scenario

The scenario takes place inside the ground floor of NOVI building, Niels Jernes Vej 10 Aalborg Øst, Denmark, as depicted in Fig. 1. The dimensions of the area are about 30 m by 16 m. There are four APs and two MSs in an indoor environment and all of them are in LOS with each other. The devices used are: two APs 3com 802.11 b/g, two APs Cisco Aironet 802.11 a/b/g and two Laptops Acer TravelMate 4000 with SMC EZ connect b/g. Two links are considered, the first between APs and MSs, and the second between MSs. The communications are performed by using the WLAN 802.11b standard.

![Figure 1. Area of the experiment.](image1)

2.2 Communication Protocol

The proposed communication protocol is described in Fig. 2 and explained in details as follows: (i) $MS_1$ measures the RSS from the available four APs; (ii) $MS_1$ searches for the existence of other MSs in the area; (iii) $MS_1$ finds $MS_2$ to which it sends its request of cooperation; (iv) If $MS_2$ accepts this request, $MS_1$ measures the RSS on the ad-hoc link with $MS_2$; (v) $MS_2$ measures the RSS from the available APs and sends this recorded data set to $MS_1$; and (vi) After receiving all the needed information, $MS_1$ starts the data fusion to estimate both locations.

![Figure 2. Communication protocol.](image2)

Note that communications between APs and MSs, intended as exchange of data, are not needed. An MS can measure the received power from every APs just by reading their broadcasted beacon signals. The communication is instead necessary between MSs, as they have to exchange their RSS information to perform the data fusion.

2.3 RSS Calibration

According to [3], it is not straightforward to translate RSS values into distances in an indoor scenario by using a conventional path loss model, because the latter should strictly reflect the specific environment in which the experiment is taking place. Therefore, in order to get valid results, the first step is to make a calibration of the RSS in the area and, consequently, to convert the received power into distance. Since the calibration of the whole area would be too time consuming, we have limited the experiment to a straight line. The results are described in Fig. 3 where the difference between transmitted power and received power is used to get the estimated relative distances.

Network Stumbler [4] has been used as a tool to record the received power at the MSs both from the infrastructure and the ad-hoc links.
2.4 Data Fusion

Fig. 4 shows the data fusion proposed in this paper. RSSD measurements are used to estimate the position of the MSs by using the Least Square (LS) algorithm. These estimates represent the initial guesses to be given in input to the Non-Linear Least Square (NLLS) and the Extended Kalman Filter (EKF). In particular, when cooperation is on, RSS measurements are used to estimate the relative distances between the MSs according to the calibration described in Section 2.3. Then, the NLLS or the EKF are used to combine RSSD with RSS measurements and increase the localization accuracy of the system.

Figure 4. Data fusion (a) without cooperation; and (b) with cooperation.

In this paper, several notations and types of distance are defined:

- \( \hat{x}^{[i]} = \left[ x^{[i]} y^{[i]} \right]^T \) \hspace{1cm} (1)
- \( \hat{x}^{(i)} = \left[ \hat{x}^{(i)} \hat{y}^{(i)} \right]^T \) \hspace{1cm} (2)

\[
\begin{align*}
\{ \Delta_k^{(i)[j]} \} & = \sqrt{\left\{ \hat{x}^{(i)} - x^{[j]} \right\}^T \left\{ \hat{x}^{(i)} - x^{[j]} \right\}} \\
\{ \tilde{d}_k^{(i)[j]} \} & = \sqrt{\left\{ \hat{x}^{(i)} - \hat{x}^{(j)} \right\}^T \left\{ \hat{x}^{(i)} - \hat{x}^{(j)} \right\}} 
\end{align*}
\]

(3) (4)

where \( x^{[i]} \) represents the coordinates of \( AP_j \), \( \hat{x}^{(i)} \) represents the estimated coordinates of \( MS_i \), \( \Delta_k^{(i)[j]} \) represents the estimated distance-difference between \( AP_i \) and \( MS_j \) at iteration \( k \) of the optimization routine when considering RSSD measurements, and \( \tilde{d}_k^{(i)[j]} \) represents the estimated distance between \( MS_j \) and \( MS_i \) at iteration \( k \) of the optimization routine when considering RSS measurements.

- \( \Delta_{\hat{d}}^{(i)[j]} = \tilde{d}_k^{(i)[j]} - \hat{d}_k^{(i)[j]} \) \hspace{1cm} (5)

\( \hat{d}_k^{(i)[j]} = d_{10}10^\left( \frac{P_0-D_{10}^{(i)[j]}}{10n} \right) \) \hspace{1cm} (6)

where \( \Delta_{\hat{d}}^{(i)[j]} \) represents the estimated distance-difference between \( AP_i \) and \( MS_j \) derived from the RSSD between the signals of \( AP_i \) and \( AP_j \) at \( MS_i \) and \( MS_j \), \( d_{10} \) represents the estimated distance between \( MS_i \) and \( MS_j \) derived from the received power \( P^{(i)[j]} \) at one of the peers, with \( P_0 \) being the received power in dBm at a short reference distance \( d_{10} \), and \( n \) the path loss exponent.

2.4.1 NLLS

The objective function to be minimized in order to determine the location of the MSs is:

\[
\mathcal{I}(\hat{x}^{(i)}) = \sum_{i=1}^n \sum_{j=1}^N \left\{ \mathcal{J}_x(\hat{x}^{(i)}) \right\}^2 + \sum_{i=1}^n \sum_{j=1, j \neq i}^n \left\{ \mathcal{J}_y(\hat{x}^{(i)}) \right\}^2
\]

(7)

where \( n \) is the total number of MSs, \( N \) is the total number of APs, and the functions \( \mathcal{J}(\bullet) \) are defined as follows:

\[
\begin{align*}
\mathcal{J}_x(\hat{x}^{(i)}) &= \left( \hat{d}_k^{(i)[j]} - \tilde{d}_k^{(i)[j]} \right)^2 - \left( \hat{d}_k^{(i)[j]} - \hat{d}_k^{(i)[j]} \right)^2 \hspace{1cm} (8) \\
\mathcal{J}_y(\hat{x}^{(i)}) &= \left( \tilde{d}_k^{(i)[j]} - \hat{d}_k^{(i)[j]} \right)^2 - \left( \tilde{d}_k^{(i)[j]} - \tilde{d}_k^{(i)[j]} \right)^2 \hspace{1cm} (9)
\end{align*}
\]

where \( (x^{[i]}, y^{[i]}) \) are the location coordinates of the reference AP, being \( AP_j \), \( (\hat{x}^{(i)}, \hat{y}^{(i)}) \) are the estimated location coordinates of \( MS_i \) at iteration \( k \) of the optimization routine.

2.4.2 EKF

There are two models that have to be defined in order to design the EKF, namely the evolution model or the motion model, which relates the previous state with the new one, and the perceptual model, which relates the measurements with the states. Assuming that the state vector is \( x_k \) and the measurements vector is \( z_k \), the motion and perception models are respectively defined as [5]:

\[
x_k = \mathcal{F}(x_{k-1}, u_{k-1}, w_{k-1})
\]

(10)
and
\[ z_k = \mathcal{H}(x_k, v_k) \]  
(11)

where \( u \) represents the external excitation vector, \( w \) is the process noise vector, and \( v \) is the measurement noise vector. The variables \( w \) and \( v \) must be independent and follow a Gaussian distribution with covariances \( Q \) and \( R \), respectively. Based on Eq. (10) and Eq. (11), the filter is given by:

**Prediction:**
\[ \hat{x}_k = \mathbf{F}(\hat{x}_{k-1}, u_{k-1}, 0) \]  
(12)
\[ P_k = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T \]  
(13)

**Correction:**
\[ K_k = P_k H_k^T \left( H_k P_k H_k^T + V_k R_k V_k^T \right)^{-1} \]  
(14)
\[ \hat{x}_k = \hat{x}_k + K_k(z_k - \mathcal{H}(\hat{x}_k, 0)) \]  
(15)
\[ P_k = (I - K_k H_k) P_k \]  
(16)

where \( P \) is the covariance error, \( A \) is the Jacobian of Eq. (10) with respect to \( x_k \), \( H \) is the Jacobian of Eq. (10) with respect to \( w_k \), \( V \) is the Jacobian of Eq. (11) with respect to \( v_k \), and \( I \) is an identity matrix of appropriate dimensions. At the first estimation, or \( k = 0 \), a value for \( \hat{x}_0 \) and \( P_0 \) needs to be initiated. Thus, a simple solution is to assume \( \hat{x}_0 \) as one of the probable states and to define \( P_0 = Q \).

In this paper, the state space is defined as the coordinates of the MSs. Therefore, the positions’ estimators at iteration \( k \) are defined as:
\[ \hat{x}^{(i)}_k = \left[ \hat{x}^{(i)}_k \ y^{(i)}_k \right]^T \]  
(17)
\[ \hat{x}_k = \left\{ \hat{x}^{(1)}_k \right\}^T \cdots \left\{ \hat{x}^{(n)}_k \right\}^T \]  
(18)

For the measurements space, \( \tau_k^{(i)} \) and \( P_k^{(i)} \) are respectively defined as the set of RSSD and RSS measurements at iteration \( k \) of the routine:
\[ \tau_k^{(i)} = \left[ \tau_k^{(i)}[2] \cdots \tau_k^{(i)}[n] \right]^T \]  
(19)
\[ P_k^{(i)} = \left[ P_k^{(i)(1)} \cdots P_k^{(i)(n)} \right]^T \]  
(20)

The full set of measurements is obtained by grouping all the measurements of the same kind in the same vector:
\[ \tau_k = \left\{ \tau_k^{(1)} \right\}^T \cdots \left\{ \tau_k^{(n)} \right\}^T \]  
(21)
\[ P_k = \left\{ P_k^{(1)} \right\}^T \cdots \left\{ P_k^{(n)} \right\}^T \]  
(22)

and then by compacting all the several types of available measurements in a single vector \( z_k \), which is given by:
\[ z_k = \left\{ \tau_k \right\}^T \left\{ P_k \right\}^T \]  
(23)

The next step is to specify the motion model and the perceptual model to be used by the EKF. By assuming that the MSs are static and there is no external excitation, the new predicted state \( \hat{x}_k \) in Eq. (10) is equal to the previous state:
\[ \hat{x}_k = \mathbf{F}(\hat{x}_{k-1}, 0, 0) = \hat{x}_{k-1} \]  
(24)

For the perception model, it is necessary to obtain the vector \( z_k \) based on the models defined by Eq. (21) and Eq. (22):
\[ \hat{z}_k = \mathcal{H}_f(\hat{x}_k, 0) = \hat{x}_{k-1} \]  
(25)

where \( \mathcal{H}_f(\bullet) \) is an entry-wise function that denotes for each entry of \( \hat{z}_k \) the appropriate function \( \mathcal{H}_f(\bullet) \) or \( \mathcal{H}_p(\bullet) \).

The last step is the determination of the process and measurements noise covariance matrices (see Eq. (13) and Eq. (14)). Since the MSs are static, it is implicit 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, \( Q \) is defined as a diagonal matrix with values of some order smaller than the expected values of the states:
\[ Q = \sigma_{xy}^2 \mathbb{I}, \quad \sigma_{xy} \ll \tilde{x} \vee y \]  
(26)

For the measurements noise, \( R \) is defined as a diagonal matrix (no correlation between measurements), which is given by:
\[ R = \left[ \begin{array}{cc} \sigma_{xy}^2 & 0 \\ 0 & \sigma_{xy}^2 \end{array} \right] \]  
(27)

where \( \mathbb{I} \) is an identity matrix of appropriate dimensions, and \( \sigma_{xy}^2 \) and \( \sigma_{xy} \) are directly derived from the available measurements:
\[ \sigma_{xy}^2 = \left[ \sigma_{xy}(1)[1] \cdots \sigma_{xy}(1)[n] \cdots \sigma_{xy}(n)[1] \cdots \sigma_{xy}(n)[n] \right]^T \]  
(28)
\[ \sigma_{xy}^2 = \left[ \sigma_{xy}(1)(2) \cdots \sigma_{xy}(n)(n) \right]^T \]  
(29)

Assuming for simplicity to consider only additive white Gaussian noise, the matrices \( W_k \) and \( V_k \) are equal to the identity matrix \( \mathbb{I} \), regardless the iteration \( k \). The matrices \( \hat{A}_k \) and \( \hat{H}_k \) represent the Jacobian of Eq. (24) and Eq. (25) with respect to \( x_k \). Since the MSs are static, \( \hat{A}_k \) is equal to the identity matrix \( I \). Taking these facts into consideration, Eq. (13) and Eq. (14) turn respectively into:
\[ P_k = P_{k-1} + Q \]  
(30)
\[ K_k = P_k H_k^T (H_k P_k H_k^T + R)^{-1} \]  
(31)

### 2.5 Results and Analysis

Before introducing the numerical results, it is worth highlighting that even though the scenario is static we have noticed several fluctuations in the measurements. This is due to the hardware and to the fact that channels 1, 3, 5, 7, 9 are used at the same time and may overlap with each other, thus causing degradation in signal quality. WLAN 802.11b divides the 2.4 GHz spectrum into 11 overlapping, staggered channels whose center frequencies are 5 MHz apart. In the standard only the center frequency of the channel and a spectral mask is specified. Since the spectral mask only defines power output restrictions up to approximately 22 MHz from the center frequency, it is assumed that the energy...
of the channel does not exceed these limits. In reality, if the transmitter is sufficiently powerful, the signal can be quite strong, even beyond the mask. It is more correct to say that given the separation between channels 1, 6 and 11, the signal on any channel should be sufficiently attenuated to minimally interfere with a transmitter on any other channel. However, a powerful transmitter on channel 1 can overwhelm a weaker transmitter on channel 6 [6]. Fig. 5(a) shows an example of received power by MS$_1$ from AP$_4$ with variations of 19 dB and standard deviation of 4.3 dB. Since this power fluctuations can introduce large estimation errors, the recorded RSS measurements have been pre-filtered by cutting the values beyond the standard deviation (see Fig. 5(b)).

The performance of the data fusion are evaluated by calculating the Root Mean Square Error (RMSE), which is defined as:

$$RMSE = \sqrt{(X_{real} - X_{est})^2 + (Y_{real} - Y_{est})^2}$$

where $[X_{real}, Y_{real}]$ and $[X_{est}, Y_{est}]$ are respectively the real and the estimated coordinates of the MS. Table 1 shows the average RMSE for all the algorithms used. The result is obtained by fixing the distance between the MSs at 2 m. It is observed that in general the NLLS and the EKF give better results with respect to the LS algorithm. Moreover, it is proven that cooperation enhances the localization accuracy with gains that go from about 43% to about 65%.

Finally, Fig. 6 shows the map of the measurements area with the estimated positions of MS$_1$. It can be noticed how the recursive EKF works differently with respect to the non-recursive NLLS. Indeed, while the NLLS treats each set of measurements independently from another, thus giving estimations spread in the area around the real position of the MS (see Fig. 6(a)), the EKF

is step-by-step converging to the real position of the MS (see Fig. 6(b)).

### Table 1. Average RMSE for used techniques.

<table>
<thead>
<tr>
<th></th>
<th>LS</th>
<th>NLLS</th>
<th>EKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooperation off</td>
<td>15.51 m</td>
<td>3.35 m</td>
<td>3.77 m</td>
</tr>
<tr>
<td>Cooperation on</td>
<td>-</td>
<td>2.17 m</td>
<td>1.61 m</td>
</tr>
<tr>
<td>Gain</td>
<td>-</td>
<td>64.61 %</td>
<td>42.72 %</td>
</tr>
</tbody>
</table>

3 CONCLUSIONS

In this paper, we have proposed an innovative solution to increase the localization accuracy in indoor scenarios. Basically, this has been achieved by allowing cooperation between mobiles and exploiting their ad-hoc communications. In particular, our aim has been to proof the concept of cooperation and demonstrate it in a WLAN 802.11b network. The numerical results exposed in the paper show that for the specific scenario assumed, our proposal can enhance the localization accuracy with gains in the range of [43%, 65%]. The future work will be mainly focused on implementing a real-time platform, and studying issues such as mobility and scalability.
Figure 6. A map illustrating estimated positions by using (a) NLLS; and (b) EKF.

References


