Experimental Localization Application in Opportunistic Scenario

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ABSTRACT

Opportunistic localization is a new approach to the self-localization problem that is recognized as one of the most critical for mobile users, in particular in indoor environments. The basic idea consists in allowing mobile users to exchange location information when they happen to be in radio range and to exploit this information in order to improve the self-localization accuracy of mobile users. This demo is aimed at proving the effectiveness of the opportunistic approach and identifying possible drawbacks and technical issues. To this end, we will realize a simple though realistic network deployment, where a mobile user, which performs a very basic min-max self localization procedure, tries to improve the accuracy of its location by communicating on an opportunistic basis with other nodes in spatial proximity. The demo will allow us to appreciate the actual benefit that the opportunistic paradigm brings to the self-localiztion problem and to compare the performance of different opportunistic localization algorithms.

Categories and Subject Descriptors

C.2.2 [**Computer–Communication Networks**]: Network Protocols

General Terms

Experimentation, Performance

Keywords

Localization, Testbed, Wireless Sensor Networks, Opportunistic Networks

1. INTRODUCTION

In this demo, we want to provide localization service for devices that do not adopt dedicated equipments. Achieving an accurate location estimation is difficult when considering cheap off-the-shelf mobile devices, particularly in indoors or urban environments. However, those nodes always have an inherent RF communication capability that can be used to communicate with other nodes and that always provide a Received Signal Strength (RSS) indicator. Thus we envision a scenario in which heterogeneous mobile nodes may have different localization accuracies obtained using information received from beacon nodes or exploiting other techniques. Moreover these nodes can communicate among themselves and exchange localization information in an opportunistic fashion, i.e. when in coverage range, and use it to update their position estimate. We want to show that these interactions among nodes can improve the localization accuracy under certain assumptions, as stated in [7, 6]. Therefore we want to compare the localization error enabling or not the opportunistic scheme. In our deployment, we will use a number of beacon nodes with known positions and channel parameters as localization infrastructure. For the sake of reducing demo complexity, some fixed nodes with variable accuracy will be deployed to emulate the opportunistic nodes that provide opportunistic interactions with the mobile nodes carried by visitors of the demo. We will adopt both range–based and range–free algorithms, in order to take into account the availability of channel parameters. In the first case, the mobile node localizes itself using the anchor nodes informations and then opportunistically it will try to ameliorate its position estimation exchanging information with the opportunistic nodes, leveraging on ranging information. If anchor nodes do not provide such parameters, the mobile node will use a range free localization technique exploiting the only position information of anchor and opportunistic nodes, at most using the RSS samples as a proximity coefficient.

2. OPPORTUNISTIC LOCALIZATION ALGORITHMS

In this demo, we will demonstrate the effectiveness of the localization results presented in [5, 6, 7] also in a real–time implementation using TmoteSky sensor nodes.

The two papers tackle the problem of opportunistic localization in two different ways.

In [7], we assumed that nodes have a 2-D Gaussian distribution of native localization error, with zero mean and a certain variance σ^2, that corresponds to a mean error of $\sigma\sqrt{\frac{\pi}{2}}$. The mobile node performs the opportunistic update after a contact with an opportunistic node that is assumed to have a better self–localization capability. To better appreciate the effect of opportunistic localization, we defined the *opportunistic gain* metric Δ_i, $i = A, B$, as

$$\Delta_i = \frac{\sigma_i\sqrt{\pi/2} - \tilde{\epsilon}}{\sigma_i\sqrt{\pi/2}}$$

where $\tilde{\epsilon}$ is the mean localization error after the opportunistic localization, whereas $\sigma_i\sqrt{\pi/2}$ is the mean localization error of the node obtained by using the native localization scheme. Therefore, Δ represents the relative gain in the localization error obtained by using the opportunistic scheme. Fig. 1 shows the performance of ML algorithm [4] but, due to its complexity, is not very suitable for tiny devices like TmoteSky. Therefore we also proposed an heuristic algorithm, very light to implement and, under certain assumptions, also effective. In this solution, we consider that the opportunistic node has only one contact with other nodes.

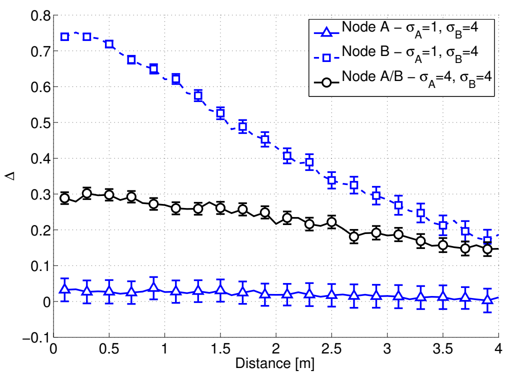

Figure 1: Relative localization error gain after an opportunistic update varying the hit distance

In [6] a different scenario is presented. A node, completely unaware of its position, collects several information from opportunistic nodes about localization. This information is then added into a matrix to create a Linear Matrix Inequality system [2]. The solution of this system is chosen as the final position estimation of the node. Also the Centroid algorithm can be used in some scenario to lighten the computational effort.

In this case, many contacts are needed to perform good localization results as shown in Fig. 2. Moreover, the information has to be obtained with the node always in the same position.

This scheme can be used both with range–free and range–based information.

Therefore it is interesting to use a hybrid approach that takes into account the number of contacts of the mobile nodes. When only one or two opportunistic nodes reply to its request, then the node performs the ML algorithm beacuse it is not possible to have a meaningful solution for the LMI or Centroid algorithm. On the contrary this solution is preferred when many communications have been collected.

3. DEMO SETUP

The demo will be performed in an area where several sensor nodes will be deployed as shown in Fig. 3.

We will consider three different classes of nodes. In the first one we have beacon nodes, that know their position

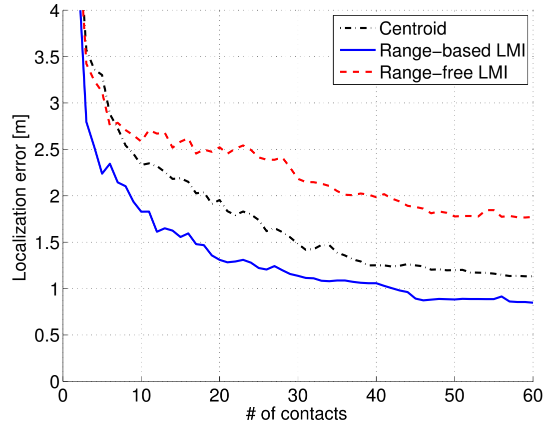

Figure 2: Localization performance of range–free LMI, range–based LMI and centroid algorithms, with $\sigma_\psi = 2$ dB and $\sigma_{loc} = 0$ m.

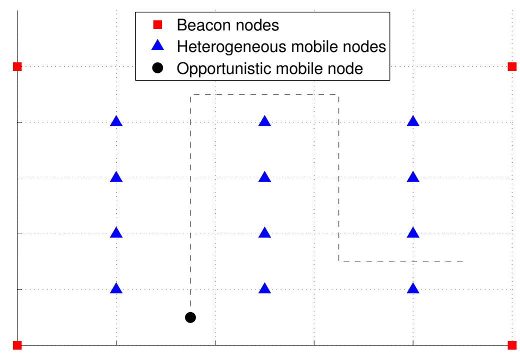

Figure 3: Nodes' deployment

and act like reference points for other nodes. In the second there are opportunistic nodes, that emulate mobile nodes and can be set with different positioning estimation accuracy to better understand the gain that we can achieve using opportunistic interactions in different scenarios. Finally, the mobile nodes, that will be carried by the visitors and that will be the target of our demonstration for localization estimation accuracy. The entire information exchanged by the mobile nodes will be processed by itself and sent to a laptot only to visualize the estimations on the screen. Moreover, we will use a pre–planned path that the opportunistic node will follow, in order to know the real position of the node while it is moving, using this information to characterize the positioning error.

In our experiments we used Tmote Sky sensor nodes [1] which are equipped with the Chipcon wireless transceiver CC2420 based on IEEE 802.15.4 standard (PHY and MAC layers). CC2420 operates in 2.4 GHz ISM band at 250 kbps, uses DSSS modulation (the encoding scheme encodes 32 chips for a symbol of 4 bits and this encoded data is then OQPSK modulated) that provides the RSSI (Received Signal Strength Indicator).

We suppose that beacon nodes broadcast every T_b seconds their position and the radio channel parameters, if available, in a coordinated way. The mobile node turns on and waits for the beacon messages in order to localize itself using Min-Max algorithm [3]. After this phase, the mobile node waits a random time T_w and then starts a scan-phase for opportunistic interactions. In the scan-phase the node transmits a request message periodically, with period T, to solicit potential neighbor nodes for opportunistic contacts. After each transmission, the node waits for a reply or for messages sent by other nodes for a fraction of time δT. The scan-phase lasts at most $N \times T$ seconds, where N is a design parameter that represents the maximum number of opportunistic updatings between two consecutive position estimations using only the beacon nodes' information.

The message broadcasted by opportunistic nodes carry information concerning the current estimated node's position, the time since the last update with self-localization methods, the time since the last opportunistic update, the class of localization accuracy the node belongs to. Furthermore, the receiver extracts from the radio signal the Radio Signal Strength Indicator (RSSI) measure, which is then used by the opportunistic localization algorithms described above.

4. CONCLUSIONS AND POSSIBLE EXTENSIONS

The demo shows that opportunistic localization paradigm is effective in enhancing the node's localization accuracy in indoor environments, though the performance increment is strongly dependent on the node's mobility patterns, the heterogeneity of the opportunistic nodes and the accuracy of the ranging. Furthermore, we prove that some of the opportunistic algorithms proposed in [5, 6, 7] are actually portable on low-end radio devices, such as Tmote-SKY sensor nodes, thus providing an effective way to enhance the localization capability of such nodes without requiring ancillary hardware. As a possible next step, we wish to investigate the potential benefits of applying tracking techniques, such as particle filters, in conjunction with the opportunistic position update schemes.

5. ACKNOWLEDGMENTS

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