Poster Abstract: A Column Matching Based Algorithm for Target Self-localization Using Beacon Nodes

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ABSTRACT

In this work, an algorithm is proposed for self-localization of a target node using power measurements from beacon nodes transmitting from known locations. The geographical area is overlaid with a virtual grid, and the problem is treated as one of testing overlapping subsets of grid cells for the presence of the target node. The proposed algorithm is validated both by Monte Carlo simulations as well as using experimental data collected from commercially-off-the-shelf bluetooth low energy (BLE) beacon nodes.

1. INTRODUCTION

Target localization in indoor environments is challenging because of the unavailability of satellite-based solutions such as the global positioning system. In the literature, several approaches have been explored for indoor localization. The RF fingerprinting based approaches (like RADAR [1], HORUS [2]) use WiFi access points as transmitters and measure the received signal strengths at various locations, and then use this radio fingerprint to determine the target location. In [3] and [4], the authors consider the so called *range-free* coarse-grained localization, where the centroid of the anchor nodes visible to the target is used to estimate its location. The recent advances in wireless sensor networks has enabled the low-cost deployment of infrastructure for specific applications such as intrusion detection, fire alarm systems, etc. In this work, a column matching based algorithm is proposed for self-localization of a target based on received signal strength (RSS) measurements from a set of low-cost beacon nodes deployed at known locations. The geographical area of interest is overlaid with a virtual grid, and the problem of localization is treated as one of testing overlapping subsets of grid cells for the presence of the target node. The accuracy of the localization is quantified in terms of the mean squared error in the location estimate. Our proposed algorithm requires very limited computing capability at the target node to determine its location, and offers comparable or better performance than existing approaches.

2. PROPOSED APPROACH

Consider a passive target located at (x_t, y_t) in a geographical area denoted by $\mathcal{A}$. To facilitate the self-localization of the target node, a set of K beacon nodes $b_1, b_2, \ldots, b_i, \ldots, b_K$ are deployed at arbitrary, known locations in $\mathcal{A}$. The transmissions from each beacon node conveys its identity and location. The target node first determines the subset of beacons it is able to receive the ids from. Then, the target node computes a binary vector based on the RSS, as explained below. This binary information of the measurements from the beacon nodes, along with an offline collected database of the RF footprint of beacon readings over the area $\mathcal{A}$ is used to localize the target, i.e., to estimate (x_t, y_t). Alternatively, if the well known path loss model for RF signal propagation is applicable in the area $\mathcal{A}$, it could be employed to construct the RF footprint database. For simplicity of exposition, in the sequel, we consider the path loss model for RF signal propagation. When a beacon node b_i transmits with a power P_0, the RSS value observed at the target node, denoted by $P_{rx,i}$, is given by $P_{rx,i} \triangleq P_0(d_0/d_i)^\eta$, where η is the path loss exponent, d_0 is a reference distance, and d_i is the distance between b_i and the target node. The target node compares the RSS value $P_{rx,i}$ with M predetermined intervals, $\left\{\mathcal{I}^{(j)} \triangleq \left(P_{th}^{(j-1)}, P_{th}^{(j)}\right] : \ j = 1, \ldots, M, P_{th}^{(0)} = P_0\right\}$, and sets the *reading* (denoted by $y_i^{(j)}$) corresponding to b_i and $\mathcal{I}^{(j)}$ using the following rule:

$$y_i^{(j)} \triangleq \begin{cases} 1, & P_{th}^{(j-1)} > P_{rx,i} \geq P_{th}^{(j)} \\ 0, & \text{else.} \end{cases} \quad (1)$$

That is, the vector $[y_i^{(1)}, y_i^{(2)}, \ldots, y_i^{(M)}]^t$ is a binary vector with either all zeros (if b_i is not "visible" at the target), or with a single 1 corresponding to the threshold interval in which the received power at the target lies. In this fashion, the target node aggregates all the $y_i^{(j)}$s to form a binary decision vector $\mathbf{y} \triangleq [y_j^{(i)}] \in \{0,1\}^{T\times 1}$, where $T \triangleq KM$ is the total number of measurements at the target.

The measurement procedure described above is mathematically equivalent to *testing* for the presence of the target node in one of the concentric annuli around the beacons, with each annulus corresponding to a different threshold interval at the target. That is, for the j^{th} comparison of the received power from i^{th} beacon's transmission, the grid cells in an annulus denoted by $\mathcal{A}_i^{(j)}$ are tested (see Fig. 1a). This can be represented by the test vector $\mathbf{a}_i^{(j)} \in \{0,1\}^{1\times N}$, where $N \triangleq L_1 L_2$ is the total number of grid cells. In $\mathbf{a}_i^{(j)}$, the entries corresponding to the cells being tested are set to 1 and the remaining entries are set to 0. Thus, the measurement process can be written as

$$\mathbf{y} = \mathbf{A}\mathbf{x}, \quad (2)$$

where $\mathbf{A} \in \{0,1\}^{T\times N}$ is the test matrix formed by stacking the row vectors $\mathbf{a}_i^{(j)}$, and $\mathbf{x} \in \{0,1\}^{N\times 1}$ indicates the true position of the target. The unknown vector $\mathbf{x}$ has exactly one of its elements equal to 1, this corresponds to the cell where the target is present.

In this work, we propose to employ the column matching algorithm from the group testing literature (e.g., [5]) to identify the location of the "1" in $\mathbf{x}$, i.e., the target location. The column-matching algorithm attempts to match the columns of $\mathbf{A}$ with test result vector $\mathbf{y}$. In particular,

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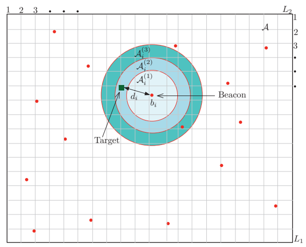
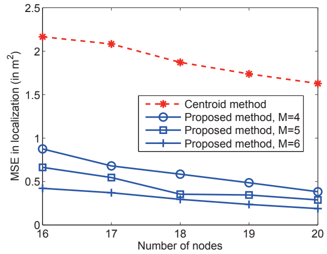
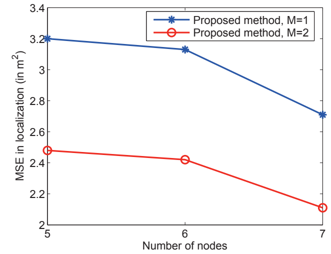


(a) Measurement process at target



(b) Monte Carlo simulation results



(c) Experimental results

Figure 1: Illustration of the measurement process at target (a) and MSE performance (b) and (c).

any column of $\mathbf{A}$ that has maximum number of entries where the 1s coincide with $\mathbf{y}$ is a potential target location, i.e.,

$$\mathcal{K} = \text{supp}\ \{\max\{\mathbf{A}^t\mathbf{y}\}\}, \tag{3}$$

where $\mathcal{K}$ is the set of potential target locations. Note that, in the target localization problem, the goal is to identify a single entry of 1, as an estimate of the target location. However, when multiple grid cells receive the beacon transmissions in the same RSS intervals, multiple grid cells return the same reading, and it is not possible to uniquely localize the target. This, in turn, leads to false alarms - multiple locations falsely identified as the target location. The probability of finding false defectives can be reduced by increasing the number of tests, $T = KM$. The tradeoff between K, M, and the accuracy of localization is studied via experiments.

3. NUMERICAL RESULTS

3.1 Monte Carlo Simulations

A given area $\mathcal{A}$ is divided into rectangular grids of sizes $(10, 10)$, $(20, 20)$, $(30, 30)$, etc. The locations of the K beacon nodes and a target node are chosen uniformly at random over the grid. The M power thresholds at the target are chosen such that the area of individual concentric annuli equal the area of the innermost disc. In the offline phase, the test matrix $\mathbf{A}$ is evaluated for a free-space path loss model ($\eta = 2$). In the online phase, the column-matching algorithm in (3) is used to identify the target locations. The simulations are performed by considering 10000 location instantiations, with identifying target location to an accuracy of single grid cell for 90% of instantiations as the performance criteria.

The MSE in localization vs number of beacon nodes for various values of threshold intervals (M) is shown in Fig. 1b. For a fixed M, the MSE decreases with increasing number of beacons, and for a fixed value of number of beacon nodes, as M increases, the MSE decreases. Also, the proposed method outperforms the centroid based method [3] for a given number of beacons.

Table 1 lists the localization accuracy achieved for various combinations of number of beacon nodes (K) and number of threshold intervals used at the target (M). For a given grid size, roughly the same number of tests ($T = KM$) are required to identify the target location to the accuracy of one grid cell with probability at least 90%.

3.2 Experimental Results

The proposed scheme is also evaluated with experimental data collected in the indoor environment. A room of size 5m $\times$ 3m is divided into 15 grid cells, each of dimension 1m $\times$ 1m. Three different setups of five, six and seven beacon nodes are considered, with beacons placed along the perimeter of the room. The beacon nodes transmit their ids on the bluetooth low energy (BLE) 2.4 GHz band at a power of $P_0 = -23$ dBm. A COTS mobile phone with BLE capability is used as the target node. At each grid location, multiple number of RSS measurements are made per beacon node. Later, 60% of the measured data is used as training data and the rest of the available data is used as the test data. At any grid cell, the RSS measurements from a given beacon node are averaged and compared with thresholds to build the test matrix $\mathbf{A}$. The MSE performance with experimental data is plotted in Fig. 1c. The plot reaffirms that using multiple threshold intervals improves the performance. Further, the experimental results successfully demonstrates the efficacy of the proposed approach in target localization to a desired accuracy level. Only a small number of beacon nodes need to be deployed and small (binary) computational resources are required at the target to estimate its location.

Table 1: Localization accuracy to within 1 or 2 grid cells.

Grid Size	K	M	T	Localization Accuracy (in %) 1 grid cell	2 grid cells
10×10	19	5	**95**	**90.5**	6.1
	24	4	**96**	**90.4**	6.7
	35	3	**105**	**90.5**	6.7
20×20	27	5	135	91.2	4.9
	36	4	144	90.9	5.0
	52	3	156	89.9	6.3
40×40	42	6	252	90.6	6.8
	54	5	270	90.1	7.0
	70	4	280	89.3	8.2

4. REFERENCES

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