Radio Frequency Based Indoor Localization in Wireless Sensor Networks

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I. Introduction and Motivation

Wireless sensor networks [1] have inspired tremendous research interest in recent years with a wide variety of potential applications on the horizon. Due to the advancement in wireless communications and Micro Electro Mechanical Systems (MEMS), these low-cost, low-power, multi-functional, tiny embedded devices can sense the environment, perform data processing, and communicate with each other over short distances. The ability to determine the spatial location of units belonging to a wireless sensor network is the starting point towards the development of many sophisticated applications, such as tracking of products and vehicles in a manufacturing plant, locating and tracking intruders in a surveillance system, patient monitoring in hospitals, wildlife habitat monitoring etc. In addition, accurate node localization in a sensor network covering a large area allows the designer for optimizing network parameters leading to optimal routing, creation of sub-network clusters for reducing power consumption etc. In that sense, accurate localization can be thought of as a primitive service required in a sensor network that can enable a variety of applications and optimization opportunities.

In this article, we describe a novel RF-based localization technique called *Ecolocation*, which was originally developed by Yedavalli et al. [2]. Ecolocation provides accurate localization without requiring the estimation of accurate channel parameters or any network pre-configuration. We also propose an extension to this original work by exploiting the idea of spatial diversity techniques in order to further improve the accuracy of localization. The Ecolocation algorithm and our proposed extension are particularly suitable for indoor environments where the presence of furniture, objects, and walls create a strongly non-linear attenuation field map that makes the use of traditional $1/r^k$ theoretical signal attenuation models ineffective.

In Ecolocation, one examines the ordered sequence of nearby reference nodes (nodes with known locations) to determine the location of an unknown node. First, an ordered sequence of reference nodes is obtained by ranking them based on one-way RSS measurements between them and the unknown node. Next, this measured sequence is compared with the ideal distance-based sequence for each location in the localization space to determine how many order-constraints are satisfied. The location which maximizes the number of satisfied constraints is estimated to be the best location of the unknown node.

Ideally, the ranks of the reference nodes based on RSS readings should be monotonic with their ranks based on true Euclidean distances. However, this is not true in the real world because of the presence of multi-path fading and shadowing in the RF channel. Reference nodes farther from the unknown node might measure higher RSS values than those which are closer, and this introduces errors in the constraints. However, it was shown that the inherent insensitivity to absolute RSS amplitudes and the inherent redundancy present in the set of constraints make this approach to localization very robust in practice. Because of the close analogy to controlling errors by redundancy in traditional error control coding, the algorithm is called *Error COntrolling LOCAlizaTION*, or Ecolocation for short.

The rest of the article is organized as follows. In Section II we give a background on the existing localization techniques in sensor networks. In Section III we describe the main Ecolocation algorithm, and in Section IV we

present our extension of the algorithm by using spatial diversity techniques. In Section V we present our experimental results and in Section VI we present our conclusions and future work.

II. Background

Over the past few years many solutions have been proposed for RF-based localization in wireless ad-hoc and sensor networks which can be broadly classified into two main categories: (1) range based, and (2) range free. Range based techniques estimate distances (range) from Received signal Strength Indicator (RSSI) measurements between the unknown node and the reference nodes and use them to triangulate the location of the unknown node, whereas range free techniques estimate the location of the unknown node without determining the range. Since the RSSI value is nowadays directly embedded in many RF chips, an RSSI-based approach is appealing for its low cost even if the position estimate is not particularly accurate.

In [3] Bulusu et al. propose a range free, proximity based solution for localization called *Centroid*, where the location estimate is the centroid of all the reference nodes which are in the proximity of the unknown node. In [4] the authors suggest an enhancement to this technique by adaptively placing reference nodes to minimize location error.

T. He et al. in [5] propose a range free localization technique called Approximate Point In Triangle *(APIT)* in which the RSSI value at the unknown node is compared with RSSI values at its neighbors and based on this comparison a decision is made whether the unknown node location is inside various triangles formed by the reference nodes. This comparison test is done for all the locations in the location space and for all the triangles that can be formed by the reference nodes. The location estimate is the centroid of the locations which are in a maximum number of triangles. The accuracy of the location estimate also depends on the non reference node neighbor density of the unknown node.

There are many Maximum Likelihood Estimation (MLE) based approaches of which [6] is a representative one, where the authors calculate the location which maximizes a likelihood function, which is based on the distance estimate and its standard deviation, using the gradient climbing method. All RF-based MLE methods need good ranging techniques that use radio frequencies to estimate distances. This either requires expensive ranging equipment and/or time consuming pre-configuration surveys of the location space.

There also exist localization techniques based on Ultra-Wide-Band technology [7], which exploits the Time-Of-Arrival (TOA) of an electromagnetic pulse. Ultrasound can be used to estimate the position with TOA of sound waves or even with the Time-Difference-Of-Arrival (TDOA) of radio and ultrasound waves. The *Cricket* system [8] claims to reach a 0.15m accuracy on a $4m \times 4m$ grid with 4 readers; such technique requires high deployment costs and ultrasound propagation is prevented by walls.

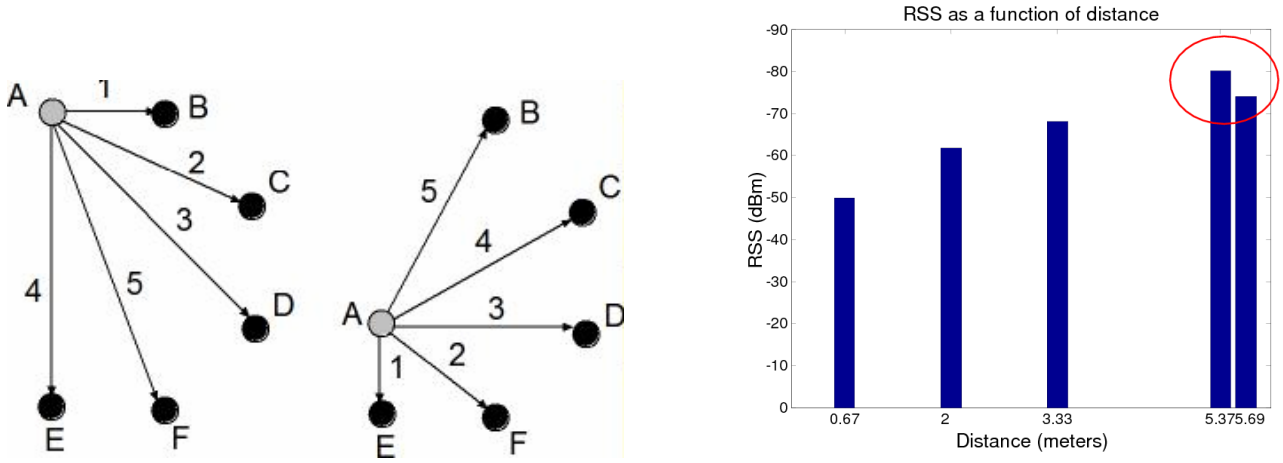
III. Ecolocation

In this section, we describe Ecolocation and illustrate it for the ideal and real world scenarios through examples. The localization process is initiated by the unknown node, possibly attached to a laptop and serving as a base station. It broadcasts a localization packet requesting the reference nodes to send a few packets. Then it collects RSSI measurements of the received packets and computes the location estimate as follows.

- Determine the ordered sequence of reference nodes by ranking them on the collected RSSI measurements.
- For each possible location grid-point in the location space determine the relative ordering of reference nodes and compare it with the RSSI ordering previously obtained, to determine how many of the ordering constraints are satisfied.
- Pick the location that maximizes the number of satisfied constraints. If there is more than one such location, take their centroid.

A. Ideal versus Real World Scenarios

Radio frequency (RF) based localization techniques are inherently dependent on the RF channel whose multi-path fading and shadowing effects have a fundamental bearing on the accuracy of location estimate. Nevertheless, it helps to study the localization technique in isolation of these effects. We introduce Ecolocation for the ideal scenario of zero multi-path fading and shadowing effects and latter explain why it provides robust and accurate location estimate even in the presence of these effects.



(a) (b)

Fig. 1. (a) The ordering of the reference nodes (B, C, D, E, F) depends on the location of the unknown node A. (b) Real Word experiment: Reference nodes farther away from the unknown node measure higher RSSI values than the closer ones.

1) Ideal Scenario: In the absence of multipath fading and shadowing, RSSI measurements between the reference nodes and the unknown node accurately represent the distances between them. If the reference nodes are ranked as a sequence in decreasing order of these RSSI values, then this order represents the increasing order of their separation from the unknown node. For a reference node ranked at position i in the ordered sequence,

$$R_i > R_j \Rightarrow d_i < d_j, \forall i < j \tag{1}$$

where, R_i and d_i are the RSSI measurement and distance of the ith ranked reference node from the unknown node, respectively. The above relationship between two reference nodes is a constraint on the location of the unknown node and is dependent on it. An ith ranked reference node forms $(i-1)$ constraints with lesser ranked ones, and for a total of n reference nodes there are $n(n-1)/2$ constraints on the unknown node.

For fixed reference node locations, the sequence order and the constraints are completely determined by the unknown node location. Figure 1(a) and Table I illustrate this idea for a simple case of five reference nodes and one unknown node. Each location grid-point in the localization space has its own set of constraints based on its Euclidean distances to the reference nodes. The unknown node location estimate can be obtained by comparing the constraints obtained from RSSI measurements to the constraint sets of each location grid-point and picking the location which satisfies the maximum number of constraints. If there are more than one such locations then their centroid is the location estimate.

TABLE I
CONSTRAINTS ON THE UNKNOWN NODE FOR THE EXAMPLE IN FIGURE 1(A)

B:1	C:2	D:3	E:4	F:5
R_1	$R_2 < R_1$	$R_3 < R_1$ $R_3 < R_2$	$R_4 < R_1$ $R_4 < R2$ $R_4 < R_3$	$R_5 < R_1$ $R_5 < R_2$ $R_5 < R_3$ $R_5 < R_4$

2) Real World Scenario: In contrast to the ideal scenario, the real world is characterized by the presence of multi-path fading and shadowing in the RF channel. Ideally, reference nodes that are far from the unknown node should measure lower RSSI values than reference nodes that are nearer, but due to multi-path effects this is not true in the real world.

Figure 1(b) shows the experimental RSSI measurements at five MICA2 receivers placed at different distances from a MICA2 transmitter. It shows that the receiver at 5.69 meters measured a higher RSSI value than the receiver

TABLE II
CONSTRAINTS ON THE UNKNOWN NODE WHEN THE RANKS OF THE FOURTH AND FIFTH RANKED NODES ARE INTERCHANGED DUE TO MULTIPATH EFFECTS.

B:1	C:2	D:3	E:5	F:4
R_1	$R_2 < R_1$	$R_3 < R_1$ $R_3 < R_2$	$R_5 < R_1$ $R_5 < R2$ $R_5 < R_3$	$R_4 < R_1$ $R_4 < R_2$ $R_4 < R_3$ $R_4 < R_5$

at 5.37 meters. Evidently, RSSI measurements do not represent distances accurately in the real world. Therefore, if the reference nodes are ranked on their respective RSSI measurements, the constraints on the unknown node location formed by these ranks will be erroneous. For example, if the ranks of fourth and fifth ranked reference nodes are interchanged due to multipath effects in the RF channel, as in the experiment of Figure 1(b), for the example in Figure 1(a), then the new constraints are as shown in Table II. As it can be seen, 10% of the constraints are erroneous in this case. The percentage of erroneous constraints depends on the RF channel condition, the topology of the reference nodes and the number of reference nodes. The unknown node location estimate accuracy in turn depends on the percentage of erroneous constraints. The inherent redundancy in the constraint set ensures that the non-erroneous constraints help in estimating the unknown node location accurately. Also, the constraint construction inherently holds true for random variations in RSSI measurements up to a tolerance level of $(|R_i - R_j|)$.

B. The Algorithm

Once the unknown node receives packets from the reference nodes, it ranks them based on their RSSI values. For ease of implementation this ranking is encoded in the form of a $n \times n$ matrix, called the RSSI matrix R, which is defined as follows:

$$R(i,j) = \begin{cases} -1, & R_i \leq R_j \\ 0, & R_i = R_j \\ 1, & R_i > R_j \end{cases} \tag{2}$$

where R_i and R_j are the RSSI values received from reference nodes i and j. In a similar fashion, for each grid point in the localization space a constraint matrix of dimension $n \times n$ is generated that encodes the relative distance ordering of the reference nodes with respect to the grid point. The elements of the constraint matrix C^k for a given grid point k are defined as follows:

$$C^k(i,j) = \begin{cases} -1, & d(i,k) > d(j,k) \\ 0, & d(i,k) = d(j,k) \\ 1, & d(i,k) < d(j,k) \end{cases} \tag{3}$$

where $d(i,k)$ and $d(j,k)$ are the distances between the reference nodes i, j and the grid point k, respectively. We describe the pseudo code of the algorithm in Figure 2.

IV. ECOLOCATION EXTENSION: EXPLOITING SPATIAL DIVERSITY TECHNIQUES

Multipath fading is probably the biggest culprit that hinders accurate location estimation using RF-based localization techniques, especially in indoor environments. In order to combat the effects of multipath and improve the reliability of transmission without increasing the transmitted power and sacrificing bandwidth, diversity combining techniques are widely used in wireless communications. These techniques require multiple copies of the transmitted signal that are uncorrelated to one another to be present at the receiver. The combined signal-to-noise ratio (SNR) is increased compared to the SNR of each diversity branch. The underlying idea is that when two or more replicas of the same signal are independently faded, then even when some of them are faded severely, one could recover the original signal from other replicas that are less attenuated. In other words, diversity techniques can significantly enhance the probability of recovering the original signal from its independently faded replicas.

We studied a possible extension of the Ecolocation algorithm exploiting the spatial diversity technique [9]. Spatial diversity is usually achieved using multiple antennas that are located sufficiently far from one another to ensure

Algorithm

Step1 : Find the grid points in the localization space that have maximum number of constraints matched.

$maxConstrMatch = 0$
for each grid point k in the localization space **do**
  Generate the constraint matrix C^k according to equation (3)
  for each element $C^k(i,j)$ in the constraint matrix **do**
    if $C^k(i,j) = R(i,j)$ **then**
      $constrMatch^{ij} = constraintMatch^{ij} + 1$
    end if
  end for
  if $constrMatch^{ij} > maxConstrMatch$ **then**
    $maxConstrMatch = constrMatch^{ij}$
  end if
end for

Step2 : Find the centroid of those grid points that had maximum number of constraints matched in Step 1.

$estX = 0$, $estY = 0$, $count = 0$
for each grid point (i,j) in the localization space **do**
  if $maxConstrMatch = constrMatch^{ij}$ **then**
    $estX = estX + i$
    $estY = estY + j$
    $count = count + 1$
  end if
end for
Estimated location: $\left(\frac{estX}{count}, \frac{estY}{count}\right)$

Fig. 2. Pseudo code of Ecolocation

independent fadings. However, it is also possible to emulate the effects of independent fading from multiple antennas by placing multiple sources very close to one another. Signals generated from these closely placed transmitters will also undergo independent fadings, and one could apply diversity techniques to recover the original signal. This spatial diversity technique could be applied at the receiver or at the transmitter end, and accordingly, it is called the *receive diversity* or the *transmit diversity*. The quality of the extracted signal depends on the way in which these different replicas are combined to increase the overall signal-to-noise ratio. The conventional selection combiner (CSC) selects the signal from the diversity branch with the largest instantaneous SNR, whereas in the maximum-ratio combiner (MRC), the signals from each channel are weighted and added together. The weight or the gain of each channel is proportional to the root-mean-square (RMS) signal level and inversely proportional to the mean square noise level in that channel. MRC is the optimum combiner for independent AWGN channels. In another category of combiners, called the switched combiner, the receiver scans all the received signals and selects a particular diversity branch with the SNR above a certain predetermined threshold. This signal is selected until its SNR drops below the threshold, at which point the receiver scans the branches again and selects a different one. Compared to the selection combiner, the switched combiner is inferior as it does not choose the best instantaneous SNR at all times. Lastly, one could also combine all the signals with equal gain, and it is accordingly called the equal gain combiner. This does not require the estimation of the fading amplitudes for each individual branch. The performance of the equal gain combiner is shown to be marginally poor than the maximum ratio combiner.

Existing empirical results have shown that there could be significant difference in probabilities of packet reception from transmitters that are only a few inches apart from each other. Figure 3, borrowed from Matt Welsh at Harvard, shows this variation in probability of packet reception from very closely placed transmitters. The observation to

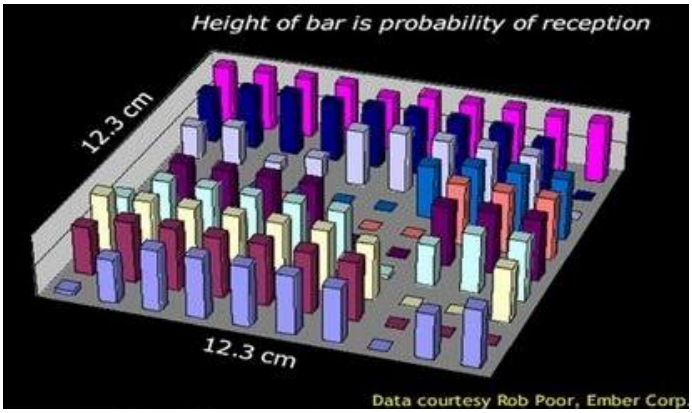


Fig. 3. Variability in probability of packet reception from transmitters that are very close to each other. Plot courtesy Matt Welsh, Harvard.

make from the picture is that, when transmitters are moved even slightly, chances of receiving signals that are severely faded or not faded at all vary to a large extent. Based on this observation, we propose an extension to Ecolocation, we propose to use the receive diversity technique, where multiple reference nodes are placed very close to each other and this cluster of nodes is treated as a single virtual node. We use three spatial diversity combining techniques: (1) conventional selection combiner, (2) a variation of equal gain combiner, and (3) maximum ratio combiner. If there are m reference nodes in cluster k, and the RSSI value received from node i is R_i for $i = 1, ..., m$, then we combine the RSSI values in the following three ways:

- Selection Combiner: It considers only the RSSI measurement that is maximum among all the nodes in the cluster; we also refer to it as the maximum RSSI combiner, i.e.,

$$R_{max} = \max\{R_1, ..., R_m\} \tag{4}$$

- Equal Gain Combiner: It takes the average of all the RSSI measurements; we refer to it as the average RSSI combiner, i.e.,

$$R_{avg} = \frac{1}{m}\sum_{i=1}^{m} R_i \tag{5}$$

- Maximum Ratio Combiner: Here we combine the signal in the following way:

$$R_{mrc} = \frac{1}{\sum_{i=1}^{m} R_i}\sum_{i=1}^{m} R_i^2 \tag{6}$$

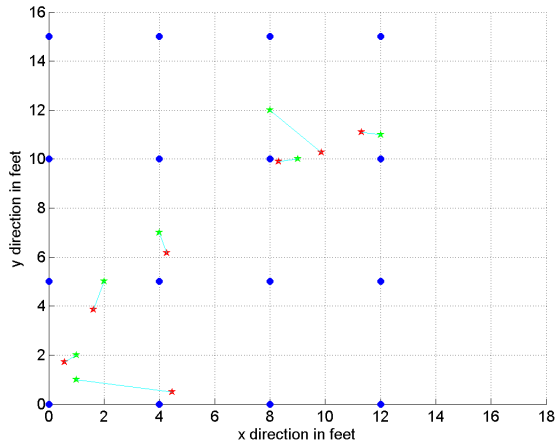
V. Experiments and Results

We took an existing implementation of the Ecolocation algorithm written in Matlab and did several experiments in the Siemens Corporate Research building using *Mica2* motes. The code that executes on the reference nodes and unknown node is written in *NesC* and runs on *TinyOS 1.x*. We also ported the Matlab code to *C* and *C#* for future integration of the algorithm with Siemens products.

In the first set of experiment, we deployed 16 nodes in the RFID lab in the form of a grid of dimension 12×15 feet. Our localization space is the whole room which is of dimension 19×17 feet (see Figure 4(a)). The x-axis and y-axis separation between the nodes were 4 feet and 5 feet respectively. We placed the unknown node at different locations within the localization space and estimated its location using the Ecolocation algorithm. Figure 4(b) shows the results. The blue dots represent the location of the reference nodes, the green dots represent the actual locations of the unknown node, and the red dots represent the estimated location of the unknown node.

In out second set, we experimented with clusters of nodes to find out the usefulness of the spatial diversity technique. We deployed 11 clusters of 2 reference nodes in each, in the form of a grid of size 10×18 feet. The x-axis and the y-axis separation between the reference nodes were 5 feet and 6 feet, respectively. We averaged over $20 - 30$ RSSI measurements from each reference nodes in order to smooth out the effects of multipath, besides the smoothing effects of clustering. Figure 5(a) shows the estimated locations and the actual locations of the unknown

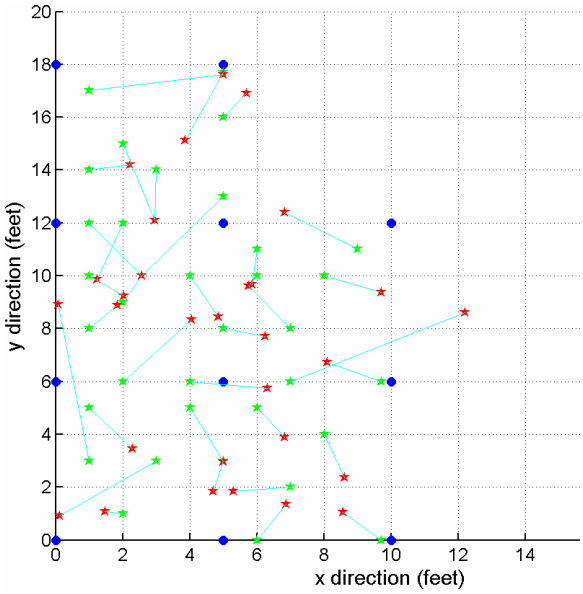
(a) Estimated locations (red dots), actual locations (green dots) and reference node locations (blue dots).



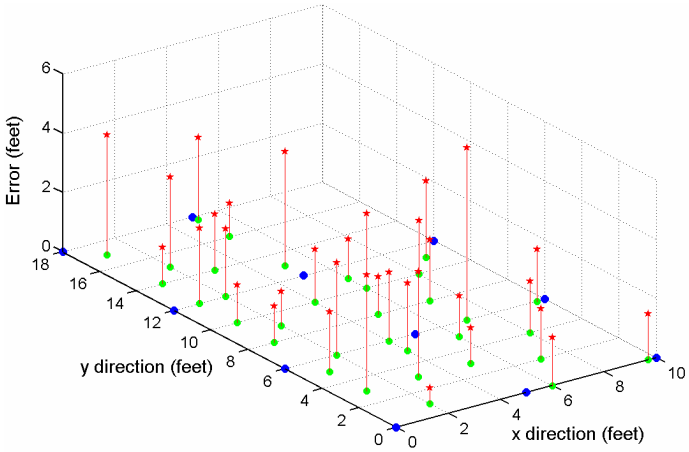
(b) Heights of the red bars signify localization errors. Green dots denote actual locations, blue dots denote reference locations.

Fig. 4. Cluster: Ecolocation experiment with 11 clusters of 2 nodes in Siemens conference room.

node along with the position of the reference nodes when the maximum ratio combiner was used to combine the RSSI values. Figure 5(b) shows the error in location estimates; the heights of the red bars denote the localization errors in feet. We compared this set of results with deploying only one reference node instead of 2 in each cluster and averaging over $30 - 50$ RSSI measurements from each node; Figure 6(a) and (b) shows the location estimates and the errors in those estimates from true locations. In Figure 7, we present the comparison of localization errors for the three different ways of combining the RSSI values: maximum, average, and maximum ratio.



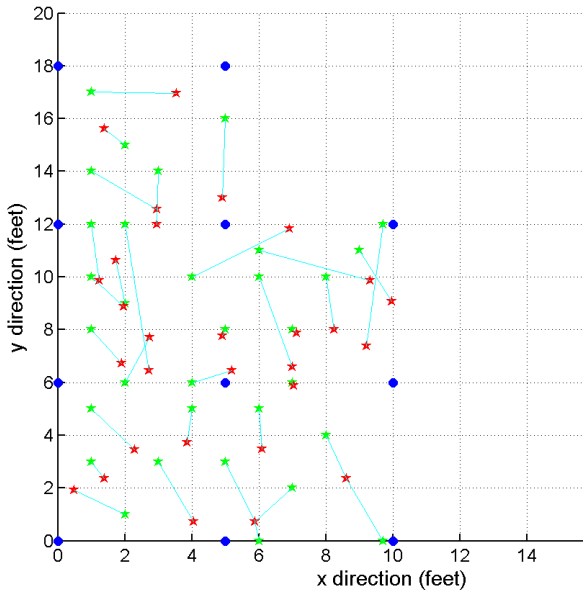
(a) Estimated locations (red dots), actual locations (green dots) and reference node locations (blue dots).



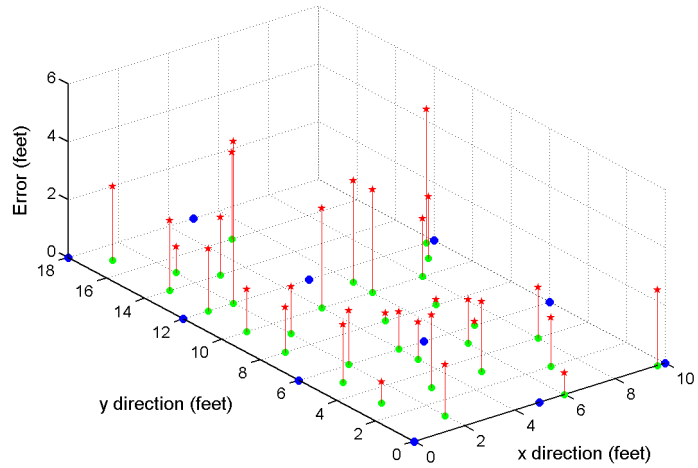
(b) Heights of the red bars signify localization errors. Green dots denote actual locations, blue dots denote reference locations.

Fig. 5. Cluster: Ecolocation experiment with 11 clusters of 2 nodes in Siemens conference room.

We also experimented with the unknown node *moving* in the localization space. Twenty reference nodes were deployed inside the lab of size 40×20 feet in approximate grid locations and the unknown node was moved from



(a) Estimated locations (red dots), actual locations (green dots) and reference node locations (blue dots).



(b) Heights of the red bars signify localization errors. Green dots denote actual locations, blue dots denote reference locations.

Fig. 6. Non-cluster: Ecolocation experiment with 11 single nodes in Siemens conference room.

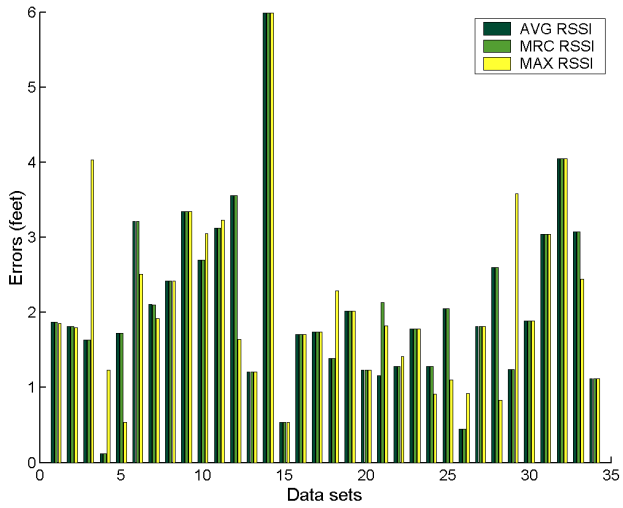


Fig. 7. Comparison of localization errors among three different diversity combining techniques.

one room to the other and back. Figure 8 shows the floor plan of the RFID lab and the estimated path of the unknown node when it was moved inside it from one room to the next and back. This was primarily done to test the effectiveness of the algorithm in the presence of mobility. We also varied the number of packets transmitted by each reference nodes to check how fast a good location estimate can be achieved. While averaging over at least 5 RSSI measurements from each node, we found that around $20 - 30$ seconds are necessary to get a good location estimate. This time could further be reduced by playing with different parameters, such as the transmission rate by the reference nodes, or scheduling them in an intelligent way. The future work lies in this direction of designing experiments to get good localization estimates in *real time* so that the moving object can be tracked.

VI. Conclusion and Future Work

In this article we described an RF localization algorithm that was originally proposed in [2], which makes use of the inherent redundancy present in the ordering of reference nodes with respect to the unknown node. Our

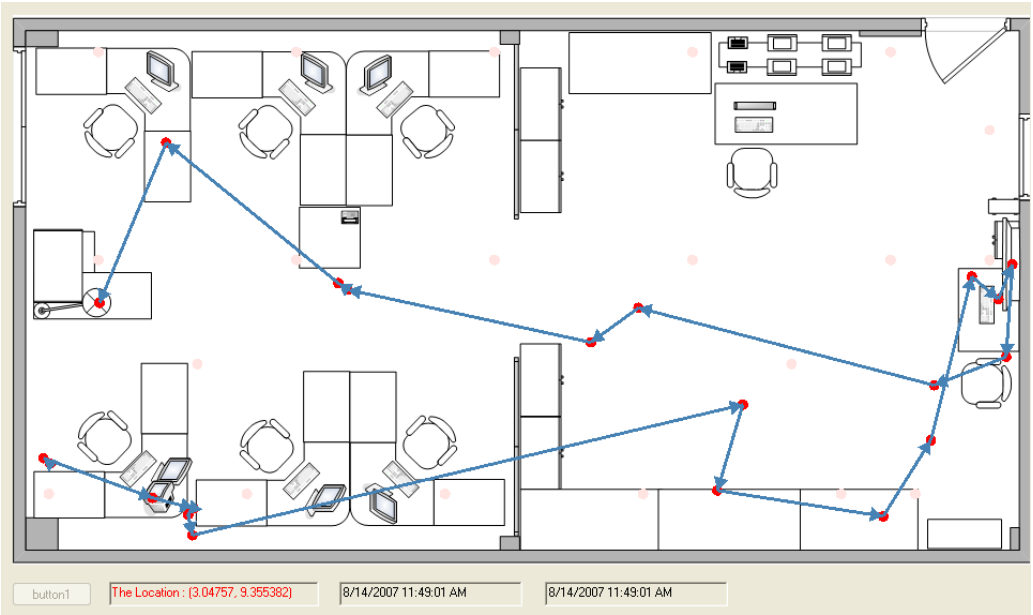


Fig. 8. Experiment with mobile node: Floor plan of the RFID lab of size 40×20 feet: It consists of two rooms, computers, desks, partition walls, and other furniture. The circles in very light color show the locations of the reference nodes. The red circles show the estimated locations of the unknown node and the lines connecting them show the estimated path of the unknown node when it was moved from the left room to the right and back.

experimental results using Mica2 nodes equipped with $CC1000$ radios verified the efficiency of the algorithm; in almost all cases the errors in localization were around 2 feet, and in some cases they were less than 1 feet. This algorithm is particularly suitable for indoor localization, where the presence of walls, furniture, and other objects attenuate the radio signals in a non-linear fashion. To combat against the multipath effects and smooth out the variations in RSSI values, we proposed an extension to the original algorithm by using the notion of spatial diversity, where multiple RSSI measurements from nodes placed very closed to each other were combined in different ways. Our preliminary experimental results using this cluster based approach showed promising results. Our future work lies in verifying this claim. We also propose to design experiments in order to get good localization estimates in *real-time* so that a moving object can be localized and tracked.

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