Localization of Servers in a Data Center Using Maximum Likelihood Identification

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Abstract—**In this paper we focus on localization of rack-mount servers in a data center and study the problem of accurately localizing unknown servers in a single rack based on the known locations of only a few servers. The current study is primarily carried out via simulations although a union bound on probability of incorrect localization is shown to be tight. Here we propose the method of maximum likelihood identification for localization of servers and show that the performance of proposed method far exceeds the performance of hyperbolic positioning. The novelty of the solution is the exploitation of geometric properties of the environment in order to obtain high accuracy localization. Results from this study will be useful in the formulation of a self-organizing networking protocol for asset tracking in a large data center.**

Key words: Hyperbolic Positioning, Maximum Likelihood Estimation ,Union Bound, Localization

I. INTRODUCTION

Identification of positions of plugged in servers in a data center is a challenging but timely business solution. In modern data centers bursty workload behavior often makes the servers quite "mobile". This means that many servers switch spots during a typical day. For example, to run power intensive applications on couple of servers, we want to place them far apart from each other, since power intensive applications generate heat. This makes asset tracking a major "pain point" and a "challenge" for IT administrators.

Traditionally for asset tracking or loclalization of a unknown node in two dimensional or three dimensional space, few nodes with known positions are required. The range estimates from all reference nodes to the unknown nodes are obtained using time of arrival (TOA) or time difference of arrival (TDOA). The position of the known node is identified as the intersection of circles for TOA or intersection of hyperbolaes for TDOA [1]. However, when range estimates incur error due to multipath and noise the traditional methods show large errors in localization [2]. In [2] maximum likelihood estimation (ML) is used to minimze the localization errors in an mobile outdoor environment. In our paper we focus our attention to problem of identification of unknown servers in a large data center. We convert the ML estimation into ML detection by exploiting the arrangement of servers and the known geometry of the racks in a data center. The rest of the paper is organized as follows.

We describe the arrangement of servers in a data center in section II. In section III we propose a maximum likelihood (ML) identification technique for localization of servers in the data center. We compare this method with a hyperbolic positioning (HBP) and show that ML identification performance far exceeds the performance of HBP. In section V we discuss the simulation results and future work.

II. DATACENTER ENVIRONMENT

In this section we briefly describe the typical arrangement of servers in the data center.

In Fig. 1 a typical arrangement of server racks in a data center is shown. The racks are 78" high, 23-25" wide and 26-30" deep and are generally placed side by side in a row without any spacing (other than a supporting beam). The x-axis denotes the row index and the y-axis denotes the rack position in the row. The z-axis (not shown in the figure) is along the height of the rack. For example $(0, 0, 1)$ denotes that the server is in row 0, rack 0 and at position 1 in the rack. Racks in two rows face each other with the aisle spacing of 48", except may be the racks in the first and the last row in the data center. Each rack in the data center may not be completely filled. A rack may hold either rack mount or blade servers. Rack mounted servers go horizontally in the rack as shown in and have typical heights of 1U or 2U where a "U" is approximately 1.8". Blade servers go verticially in the rack.

The process of server localization starts with the assumption of a few servers in the known locations. Using the servers in the known locations we localize all the plugged in servers in the current rack whose postions are unknown. We also localize few servers in the next rack

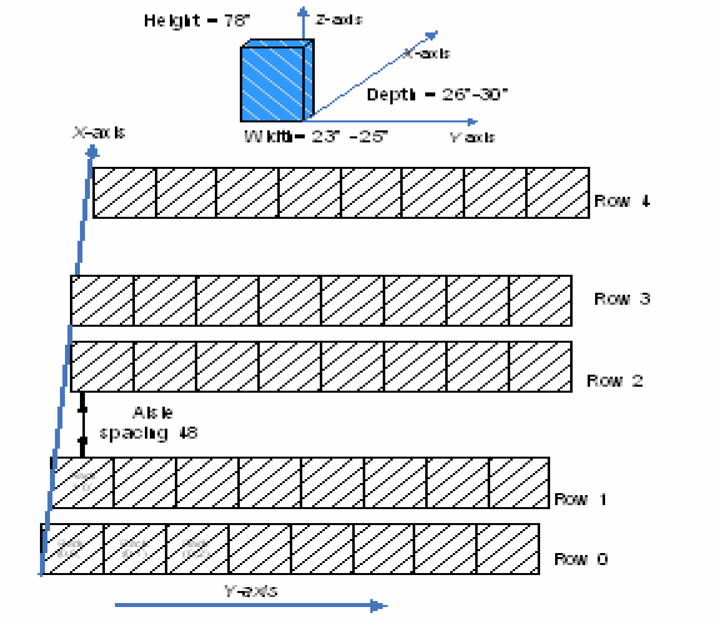

Fig 1. Arrangement of Servers in a Datacenter

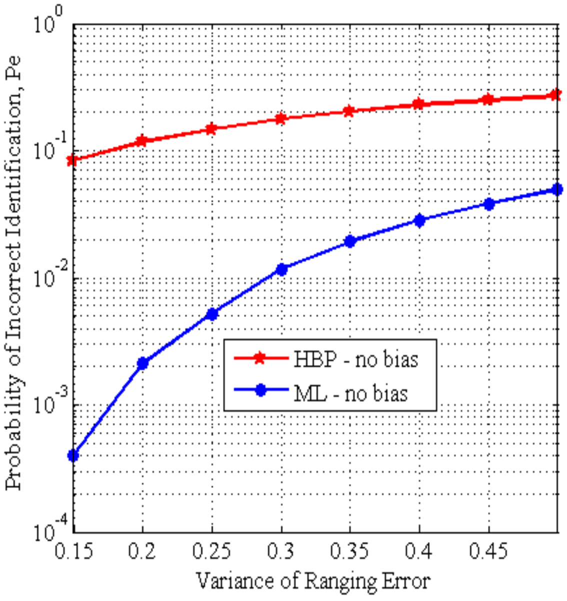

Fig 2. Performance Comparision of HBP and ML

which are used as known servers for subsequent rack localization. Thus we complete localization of servers in one rack at a time and then proceed to the localization of next row . Details of this protocol will be analyzed in future a publication.

In the reminder of this paper we restrict our attention to localization of 1U servers in a single rack. The loclaization of blade servers and the geometry of racks other than rectangular shape will be addressed in the future work.

III. LOCALIZATION TECHNIQUES

Ranging refers to the method of computing the distance between the reference node and the target node. To obtain range estimates, UWB radio, which has a potential to provide high accuracies of few inches [3], [5], could be used. Range estimates can be obtained by measuring signal strength or estimating the TOA. Localization involves determining the position of a target in 2 or 3 dimensional space with the help of reference nodes.

A. *Hyperbolic Positioning*

Hyperbolic Positioning technique requires common time reference only between refernece nodes and does not rely on the synchronization between references nodes and the target node [4]. The position of the target node is determined based on the time difference of arrival from two reference nodes. Let us determine the 2-D position of the target node $T(x_0, y_0)$ using k reference nodes. Each of the reference node makes the range measurement based on TOA with the target node denoted as $D_{1T}, D_{2T}....D_{kT}$. Let us assume that the reference node shares a common time reference and the clock at the target node T is delayed by δ. Then it is observed that the difference of range measurements between any pair of node removes the delay. The difference of range measurement between any two nodes is given as

$$D_{kT} - D_{(lT} \;= c(\tau_{kT} + \delta) - c(\tau_{lT}, +\delta) \tag{1}$$

where τ_{kT} denotes the TOA measured by reference node k from the target node. The position of target node T in the 2-D space is determined by the intersection of hyperbola. For Localization in 2-D using TDOA, we require atleast 3 reference nodes. However, when range measurements incur errors due to multipath and noise HBP could show large errors in localization [2]. Infact, in this case when the estimation problem is converted into a detection problem ML detection shows much better accuracies than HBP loclaization, as will be shown in section V

B. *Maximum Likelihood Estimation*

We assume that for each server an estimate of its location is determined independent of other estimates. In a rare situation of two or more nodes claiming the same location on a rack, further transmission between the nodes need to be done in order to iron-out the contention.

To explain the location detection algorithm, which is derived using hypothesis testing, consider only two transmitters at known locations in rack 0 and one in rack 1 of row 0 (this can be easily extended to *p* transmitters). Each of the known nodes measure the distances using TOA from an unknown node at $(0, m, l)$ as d_{1ml},d_{2ml}, d_{3ml} respectively. Here $m \in (0, 1), l \in (0, 1, 2...N-1)$. A maximum of Q out of $2N-3$ (N possible positions for rack 1 and $N-3$ possible positions for rack 0, as 3 positions are occupied by the known transmitters) possible positions are filled by plugged-in servers. Each of the Q nodes will estimate its position based on its range measurements from the three transmitters. Let us consider the detection of the location of one of these Qnodes. For simplicity, call this node as node *u*. Since it does not know its location, it hypothesizes its location to be any one of the possible locations and forms $2N-3$ likelihood functions, one for each hypothesis, based on the measured data (r_{1u}, r_{2u}, r_{3u}). For forming the likelihood function, we assume that a range estimate is distributed as Gaussian with zero bias and variance $N_0/2$. This model assumes line of sight propagation, which may be reasonable when the transmitters and the receivers are in close proximity of each other. Later on we relax this assumption and intorduce bias in the range estimates. The bias is introduced only if the true range exceeds 1m. This is valid since based our measurements we found that the bias does not necessarily depend on distance and is negligible for small distances [7]. The node u estimates its location based on the maximum likelihood rule, i.e., decide location $(0, u,v)$ where

$$(u, v) = arg_{(\psi,\phi)} \quad max \quad p\left(r_{1u}, r_{2u}, r_{3u} | H_{ml}\right), \tag{2}$$

$$\psi = (m \in (0,1), l \in (0, 1..N-1))$$
$$\phi = (m, l) \notin \{(0, y_1), (0, y_2), (0, y_3)\}$$
$$p\left(r_{1u}, r_{2u}, r_{3u} | H_{ml}\right) =$$
$$\frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{-\frac{1}{2\sigma^2}\sum_{k=1}^{3}\left(r_{ku} - d_{kml}\right)^2\right\} \tag{3}$$

An equivalent decision rule is given by the minimum distance rule.

Since each plugged in server is classified as occupying one of the allowed server positions, several types of errors could happen. A server could be misclassified to be occupying a wrong position where (i) there actually exists another server or (ii) there exists no server. Another situation occurs when two or more nodes claim the same location. This situation could be resolved by subsequent range measurements. For the proposed location estimation system to be successful, it is imperative that the probability of error in the classification of a node is extremely small, especially because the estimation of nodes occurs in successive stages, relying on previous estimates, one rack at a time and one row at a time. We briefly mention the calculation of probability of correctly identifying a node location for the maximum likelihood rule. By expanding eq. 2 and by throwing out the terms that do not depend on *m,l*, the equivalent rule picks the maximum of $Z_{m,l} = \langle r, d_{ml}\rangle - E_{ml}/2$, where $\mathbf{r} = (r_{1u}, r_{2u}, r_{3u})^T$, $d_{ml} = (d_{1ml}, d_{2ml}, d_{3ml})$ denotes the inner product between two vectors and $E_{ml} = \langle d_{ml}, d_{ml}\rangle$. Given that the true location of node u is, say, *(t, w)*, the probability of correct classification is the probability that $Z_{t,w}$ is the largest among all possible Z_{ml} , where $\mathbf{r}$ is distributed as Gaussian with mean vector d_{ml} and variance-covariance matrix $\sigma^2 I$. Finally, a closed expression for error probabilities is similar to calculation of error probabilites in the detection of an M-ary signal in additive white Gaussin noise with an aribtary signal set [6]. The exact error probability is difficult to calculate but excellent upper and lower bounds which are tight at low SNR are available [6].

Notice that the maximum likelihood rule does not require the knowledge of the variance, as long as the variance is the same for any estimated range. If the variances of the range estimates depend on the distance, then the maximum likelihood rule would require the values of these variances. However, for short distances, spanning the height of a rack or an adjacent rack, a single variance assumption may be valid as a first approximation [7]. For assessing the effectiveness of the algorithm we will use MATLAB simulations and union bound discussed in section IV. Simulated range estimates based on normal distributions will be used for arriving at the correct decision. Location estimation accuracy will be determined by computing the fraction of times the correct transmitting nodes was identified through the proposed algorithm. When an incorrect identification occurs, the algorithm will likely identify one of the neighboring locations as the transmitting node. This conjecture is verified in our simualtion study in section V. Since the algorithm operates on a sequential mode of estimation from one rack to the next and so on, a key performance index will be the effect of error propagation on the accuracy of localization of subsequent servers. We believe that if the probability of an incorrect identification of a server is kept within a very small number, the error propagation effect can be contained.

IV. ERROR BOUNDS

For any contable set of events, $A_1, A_2, ...$, the probability of union of one or more events is no greater than the sum of probabilties of individual events

$$P_r(\bigcup_i A_i) \leq \sum_i P_r[A_i]. \tag{4}$$

Thus the probability of error that u is localized to be node i is given by

$$P\left(\varepsilon|\mathbf{s}_u\right) = P_r\left[\bigcup_{i\neq u} \varepsilon_{ui}|s_u\right] \tag{5}$$

where

$$\mathbf{s}_u = \left(s_{1u}, s_{2u}, s_{3u}\right), \tag{6}$$

$$P\left(\varepsilon_{ui}|\mathbf{s}_u\right) = Q\left(\frac{||\mathbf{s}_u - \mathbf{s}_i||}{\sqrt(2N_0)}\right), \tag{7}$$

$$||\mathbf{s}_u - \mathbf{s}_i|| = \sqrt{\sum_{k=1}^{3}\left(s_{ku} - s_{ki}\right)^2}. \tag{8}$$

s_{ku} is the distance between a known server at a node *k* and the server *u* to be localized .

s_{ki} is the distance between any known server *k* and one of the possible hypothesised positions of the servers.

Applying union bound [6] gives

$$P\left(\varepsilon|s_u\right) \leq \sum_{i\neq u} P\left(\varepsilon_{ui}|s_u\right). \tag{9}$$

If *M* corresponds to the number of possible unknown positions, the average probability fo error is given as

$$P\left(\varepsilon\right) = \frac{1}{M}\sum_u P\left(\varepsilon|s_u\right). \tag{10}$$

V. SIMULATION SET UP AND RESULTS

We simulate HBP and ML estimation techniques described in section III. In the simulation, we consider only two racks in the data center, rack 0 and rack 1. We study the problem of loclaization of 1U servers in the rack 0. We estimate the performance of these techniques by estimating the probability of incorrect indetification of server position P_e. We also estimate the probability that the algorithm picks erroneously one of the neighbors as the correct position P_{en}. In both the techniques 3 known server positions are used, two in rack 0 (in the middle and bottom of the rack) and one in the middle of rack 1. *i.i.d* Gaussian errors are added to the true value. Given the dimension of the rack, there are 42, IU servers in rack 0 out of which a maximum of 40 server positions may be unknown. We assume that the rack is completley filled and thus all possible server positions are known. In HBP simulation, the position of each of the unknown server is estimated using the distances from 3 known servers(using TOA). The position of unknown server is determined using the intersection of hyperbola. In HBP the position of the unknown server is found in the nearest neighbor sense by finding the minimum distance between the estimated position and all the possible server positions.

Results obtained through simulation are shown in Fig. 2 through Fig. 6. In Fig. 2 the perfromance of HBP method is compared with ML detection method. Assuming zero bias in the range estimates, the averarge probability of errors in identification of locations of unknown servers in a rack is plotted as function of variance of ranging errors. It can be seen that the ML method significantly outperforms the HBP method. Whereas the ML method requires the calculation of distances between the three known nodes and all possible hypothesized positions for the unknown node, the HBP method requires only the finding of the nearest neighbor node, nearest to the estimated position arrived through hyperbolic intersection. Hence, the ML method requires more computation per sever localization. However, since computations involve mainly the calculations of Eucledian distances and ascertaining the minimum of a set of numbers, these computations can be done quickly with a reasonable inexpensive processor. Certainly, the proposed localization algorithm dictates an accuracy that is not attainable with the HBP method. In the remaining figures we show only the performance of the ML method.

Fig. 3 shows a comparison of the probability of errors based on simulation study and the union bound. It can be seen that, as long as the variance is below 0.8 (corresponding to a probability of error of less than 0.1), the union bound is extremely close to the simulation estimate. At a variance of ranging error of 0.15, the probability of error is less than 0.001.

Fig. 4 shows the error probability of ML method as a function of node position, for two different variances of ranging errors. It can be seen that the nodes at the ends of a rack experience less probabilities of incorrect identification than the nodes at the bottom or the top of the rack. Of course, each of the two end nodes, the top and the bottom, has only one immediate neighbor, and this could have contributed to the low error rate.

Fig. 5 shows the effect of bias in the ranging error on the probability of error of the ML method. Bias is intorduced whe the range exceeds 1m. It can be seen that the bias plays a significant role, with a bias of less than 0.5 at a variance of 0.15 being needed in order to have an acceptable probability of less than 0.002. If ranging errors show bias higher than 0.5, some sort of bias reduction technique, perhaps through multiple measurements among the known servers would be needed.

The bar chart in Fig. 6 shows the comparison of the two error probabilities, P_e and P_{en}. Identical values of these, as seen in the simulations, show that whenever an incorrect identification of a node happens, with a very high probability, the node is incorrectly localized to be an immediate neighbor of the correct location. This behavior of the ML algorithm, along with the possibility of low probability of error with better range estimation errors, would contain the error propagation in localizations from a rack to another rack and allow for the proposed localization protocol to be successful. Further analysis of error propagation effect will be carried out in a future study.

VI. CONCLUSION

In this paper we studied the problem of localization of rack mount servers in a datacenter. The loclaization is carried out by using few servers in known location. An error performance study on the localization of all plugged-in servers in a single rack was done. Using a simulation study, both the traditional hyperbolic positioning (HBP) and maximum likelihood identification (ML) were tested with respect to the probabilities of incorrect identification of a server position. Our preliminary analysis indicates (i) the ML method is far superior to HBP in terms of accuracy of localization (ii) the ML method, though computationally more intense than HBP, is executable with cheap processors (iii) even with ML method, the overall accuracy critically depends on good range estimates between a pair of UWB radios. Future study would involve bias and variance reduction techniques in arriving at quality range estimates based on time of arrival measurements and the effect of error propagation on localization of servers in subsequent racks.

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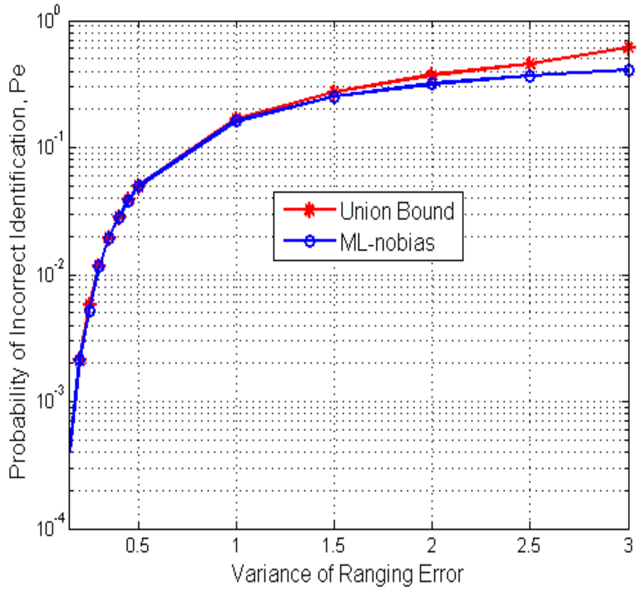

Fig 3. Union Bound P_e for ML method

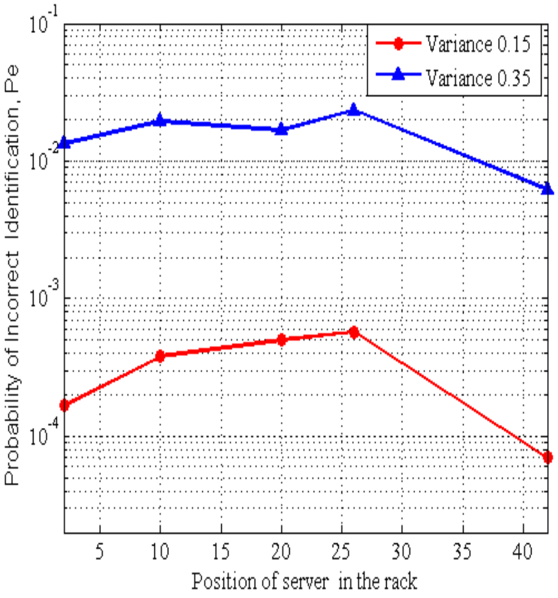

Fig 4. Effect of Server Position on Probability of Incorrect Identification

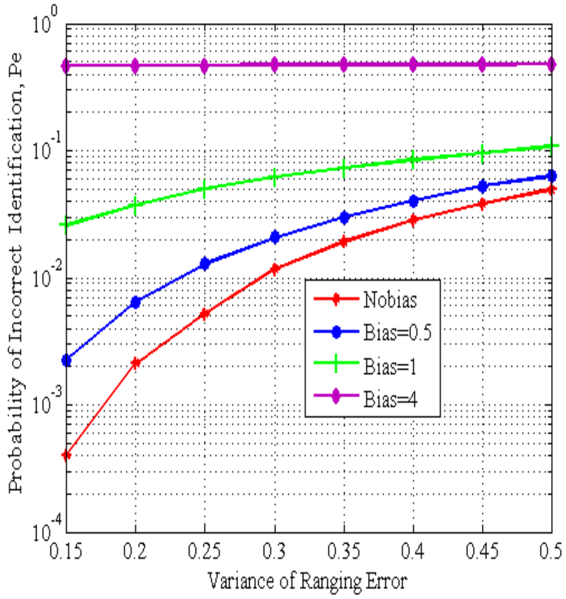

Fig 5. Performance of ML Method with Bias in Range Error

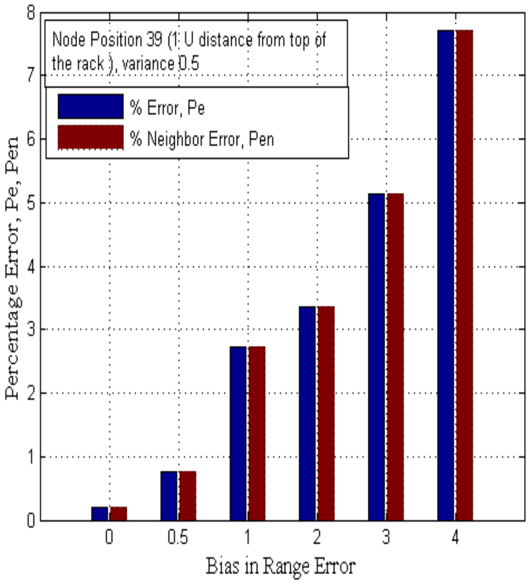

Fig 6. Percentage Errors with Bias in Range Estimates.