A NOVEL COOPERATIVE LOCALIZATION ALGORITHM FOR INDOOR SENSOR NETWORKS

Nayef A. Alsindi, Student Member IEEE, Kaveh Pahlavan, Fellow IEEE, Bardia Alavi, Student Member IEEE
Center for Wireless Information Network Studies
Electrical Engineering Department
Worcester Polytechnic Institute
Worcester, MA 01609, USA
{nalsindi, bardia, kaveh}@wpi.edu

Xinrong Li, Member IEEE
Department of Electrical Engineering,
University of North Texas
Denton, Texas 76203, USA
xinrong@unt.edu

ABSTRACT

Recently, node localization for multi-hop sensor networks has attracted considerable attention. In these networks, error propagation provides a serious challenge to algorithm development and accuracy of final location estimates. In this paper we introduce a novel computationally efficient distributed algorithm, Cooperative Localization with Optimum Quality of Estimate (CLOQ) which takes advantage of the behavior of the channel to provide accurate indoor positioning. This algorithm uses the quality of ranging and positioning estimates to provide practical and accurate results and more importantly reduce error propagation substantially. Using UWB measurements and modeling of the ranging error in a typical office building we compare the performance of this cooperative localization algorithm with a non-channel based algorithm for indoor ad-hoc sensor environments.

KEYWORDS

Ad-hoc sensor wireless networks, cooperative localization, indoor positioning, ultra-wideband, channel modeling

I. INTRODUCTION

In recent years there has been great interest in ad-hoc sensor networks for a variety of applications. The development of MEMS technology and the advancement in digital electronics and wireless communications have made it possible to design small size, low-cost energy efficient sensor nodes that could be deployed in different environments and serve many applications [1]. Among those are military, commercial, public safety, environmental, health and home applications.

Ad-hoc sensor applications in general require position information for routing, energy management and application-specific tasks such as temperature and pressure monitoring, etc. The nature of the application usually dictates specific requirements that have to be met by the ad-hoc sensor positioning algorithms. For example deploying hundreds of nodes in a forest faces different challenges as opposed to trying to locate sensors inside a building for military applications. The challenges for indoor positioning in particular face severe multipath fading and harsh indoor propagation environment. As such, accurate indoor localization suffers from large ranging errors caused by undetected direct path conditions [2, 3]. To develop practical and accurate localization algorithms the behavior of the channel cannot be neglected.

In literature there are different methods that provide localization solutions for ad-hoc sensor networks. In [5, 6] the major drawback is the reliance on external infrastructure and their centralized approach in position estimation. GPS-free positioning provides sufficient accuracy for basic network functions and relative positioning since no beacons/anchors are used [7]. Distributed positioning algorithms reported in [8, 9, 10] provide the best alternatives so far, in their approach. The algorithms are robust, self-organizing and energy efficient. However, there is one major weakness among all the aforementioned solutions; which is the lack of realistic modeling of the wireless propagation channel. In addition the application scenario is non-specific and as such doesn’t take the channel condition into consideration. Understanding and modeling of the channel is of utmost importance to the accuracy of positioning solutions. Algorithm development from a networking perspective without understanding of the channel can complicate the design process and provide solution with inadequate accuracies.

In this paper we focus on cooperative localization for indoor ad-hoc sensor applications; where the modeling of the indoor propagation channel is integrated in the algorithm development. Thus, the ranging error between sensor nodes is realistically modeled. In addition, we take advantage of the information obtained from the channel in order to minimize the positioning error and limit the propagation of errors throughout the ad-hoc sensor network. As such, we introduce a novel algorithm, Cooperative Localization with Optimum Quality of Estimate (CLOQ). It is based on iterative multi-lateration approach which provides a way to expand the coverage of the network in a step-by-step fashion. The order in which nodes transform themselves to anchors and estimate their position is the core of CLOQ. The algorithm takes advantage of the distance measurement error (DME) and Path-Loss (PL) models developed at the Center of Wireless Information Network Studies (CWINS) using Ultra-Wide Band (UWB) measurements in a typical indoor office environment; where the channel conditions effect on the position estimate is categorized.

The structure of the rest of the paper is as follows. Section II describes the models used for algorithm development. Section III introduces CLOQ algorithm and highlight its different features. Section IV describes the simulation and the results. Finally section V provides the conclusion and future work.
PL and DME models used in the algorithm development in indoor environments. In this section a brief description of the novel, realistic channel models, recently developed at CWINS [4]. As a result the methodology followed in this paper utilizes the received direct-path (DP) since it determines the TOA which is in turn related to the DME. Figure 1 explains the difference between modeling of total received power versus received DP power. Notice that the former decays much slower than the latter, mainly because after a certain distance the DP dies while total received power is still available from other multipath components. A path-loss model for the DP is needed because it provides the coverage for accurate ranging, while models for the total power provide communication coverage. The modeling framework was first reported in [4]. The distance-power gradient is usually determined from measurement data using least-square (LS) linear regression. The partitioned model is defined as follows,

\[ L_p = L_0 + \begin{cases} 10\alpha_1 \log_{10} d + \sigma_1, & d < d_{bp} \\ 10\alpha_2 \log_{10} d_{bp} + 10\alpha_2 \log_{10} \left( \frac{d}{d_{bp}} \right) + \sigma_2, & d \geq d_{bp} \end{cases} \]

where \( L_p \) is the path-loss in dB, \( L_0 \) is the first-meter path-loss, and \( d_{bp} \) is break-point distance. The path-loss is modeled with two different distance-power gradients \( \alpha_1 \) and \( \alpha_2 \), for before and after the break-point, respectively [14]. The break-point designates the dividing point for LOS and non-LOS (NLOS) channel conditions. The values for the 3 GHz PL model are given by \( L_0 = 42 \) dB, \( d_{bp} = 10 \) m, \( \alpha_1 = 4.2 \), \( \alpha_2 = 8.7 \), \( \sigma_1 = 14.5 \) dB and \( \sigma_2 = 12.1 \) dB.

A. Path-Loss Modeling

In traditional path-loss modeling the decay of the total received power is best fitted with linear regression method to calculate a unique or partitioned distance-power gradient [14]. However in TOA-based positioning applications, in addition to the modeling of the total power, there is a need to model the ranging errors which is critical to the accuracy in positioning applications.

B. Distance Measurement Error Modeling

A novel DME model first introduced in [4] places a greater emphasis on the behavior of the DP. When the sensor node is close to the reference point, the power of the DP (\( P_{DP} \)) is very strong. As a result, the first path can be easily detected which means very accurate ranging. This region of operation is usually referred to as Detected Direct Path (DDP). However as the node moves away from the reference point the strength of the DP decays gradually, where it reaches a region where the DP is no longer as strong. In fact it is weakened and in certain instances it would be Undetected Direct Path (UDP). Figure 2 further explains the three region DME model.

In the second region, a mixture of DDP and UDP conditions provide acceptable ranging but occasionally large errors. Finally when the DP can no longer be detected the third region of operation is known as UDP; where it suffers the most errors. As such it exhibits the worse ranging accuracy. Note that in all the previous mentioned regions, the total power is usually much higher than the DP power. When the sensor
node’s total received power falls below a certain threshold, then it is operating in the No Coverage (NC) area; where neither positioning nor communication can take place. The DME model introduces 3 regions with different statistical behavior. Namely a Gaussian mean ($\mu$) and variance ($\sigma^2$) characterizes each region of operation. The 3 GHz DME model is given by the following expression:

$$N(\mu, \sigma^2) = \begin{cases} N(0.1, 0.01) & P_{dp} \geq -90 \text{dBm} \\ N(0.4, 0.09) & -90 > P_{dp} \geq -105 \text{dBm} \\ N(1.0, 1.96) & -105 > P_{dp} \geq -115 \text{dBm} \end{cases}$$ (2)

## III. CLOQ Algorithm

Integrating the channel condition into the positioning algorithm development is necessary for accurate localization. As a result CLOQ takes advantage of the PL and DME modeling efforts introduced in section 2. The algorithm is a more practical approach to the ad-hoc positioning problem that is based on recursive position estimation. It is an iterative multi-lateration approach which provides a way to expand the coverage of the network in a step-by-step fashion. Usually a subset of the deployed nodes knows their exact position a priori. In this paper, original anchors placed outside of the building will be referred to as Reference Points (RP), while the iteratively elected anchors will simply be called anchors. In addition to iteratively increasing the number of anchors, this algorithm ensures that the error propagation doesn’t escalate through the network. In fact the as will be shown in simulation later very accurate positioning is achievable. In this section, the algorithm parameters will be introduced followed by a detailed algorithm description.

### A. Algorithm Parameters

**Quality of Link (QoL):** This parameter is a representation of the channel condition at any instance between two nodes in an ad-hoc environment. In other words, it is a statistical measure characterized by the variance derived from the DME model introduced in Section 2. More specifically $QoL = \sigma_i^2$, where $i$ represents one of the three quality regions in the DME model. The translation of the received power of the first path to the DME model parameters such as the mean and variance is given in (2). QoL helps to establish a statistical measure of the node-to-anchor channel conditions. In an ad-hoc setting a node will be covered by a number of anchors each with a respective QoL associated with it. From the QoL, the node will be able to determine which anchor to choose for triangulation in order to minimize its position error.

**Quality of Estimate (QoE):** In recursive position estimation, nodes compute their position through triangulation. Nodes then become anchors and broadcast their own position. What would happen to the error propagation if nodes use anchor coordinates that are erroneous? How can a node quantify the quality of its own position estimate? In order to answer these questions and establish an algorithm that reduces error propagation, the node to anchor transition must be controlled. This control is inherent in the QoE index which provides a sensor node with relative measure of the quality of the position estimate at the time of triangulation. The index provides a mapping of the statistical channel condition for each link to the accuracy of the position estimate. QoE is formed by combining the different QoLs between a node and 3 anchors for a 2-dimensional scenario. Table 1 shows the QoE indices relating to the 10 conditions a node can see along with simulation results that provide average and maximum position errors for each QoE case. As the table shows, both the average and maximum errors are highly correlated with the QoE.

### B. Algorithm Description

The main contribution of CLOQ is two-folds. The first is integrating empirical UWB channel measurements and modeling efforts in developing a realistic algorithm. The second is using these efforts in developing an algorithm that controls and minimizes the error propagation through an ad-hoc sensor network. In order to understand the working of the algorithm it is first important to analyze the reasons why error propagates in the first place. In any instance that a node wants to triangulate its position, several factors usually affect the accuracy of the results. The physical geometry of the nodes, the ranging error and the anchor position errors all introduce some error in the final position estimate.

As a result each time a node upgrades to anchor; the error in the position estimate is propagated to the other nodes in the network. The next logical question is: which factor has a bigger impact on the error of the position estimate of the node? Is it the ranging error or the error in the position of the anchors? The answer to this question is very essential to the CLOQ algorithm since it determines the basis of the selection criteria. Figure 3 shows a simulation that answers the above questions. The results of the simulation shows that when the anchors have very small position errors in their coordinates (Figure 3a) but large ranging errors, the result of the triangulation contains large amounts of uncertainty. On the other hand, Figure 3b shows that even with large errors in the anchors’ positions, small ranging errors produces much more acceptable triangulation uncertainties. The stark difference highlights the impact of the ranging error on the position estimate. This important conclusion will dictate the overall structure of the algorithm as will be described next.
CLOQ algorithm currently works in a 2-dimensional setting, but extension to 3-dimensional case is trivial. The major difference between them is that Table 1 has to be updated to incorporate the fourth anchor into the computation of the QoE. The algorithm is composed of four stages: anchor selection, position estimation, anchor nomination and new anchor incorporation.

**Stage 1: Anchor Selection**
In this stage the node is listening to the channel for candidate anchors so it can triangulate its own position and perhaps be eligible for upgrading itself to an anchor. If it receives ranging packets from more than 3 anchors then it ranks them according to the QoL between the node and that anchor since this is more important than QoE for anchor selection as shown in Fig. 3. If QoL to several anchors is the same then the node has to sort them according to the QoE of the anchors. Then the best three anchors are selected for triangulation and computation of QoE. This is best illustrated in an example. Figure 4 illustrates this anchor selection criterion.

Node D listens to the channel and hears from 5 different anchors. The original RP’s have a QoE of 0 since we assume that they know their location exactly. Node D ranks the anchors according to the QoL, and if there are similar QoL’s then it ranks them according to the QoE of the anchor. In this case, node D will choose anchors RP2, A and C for triangulation and computation of QoE. This is best illustrated in an example. Figure 4 illustrates this anchor selection criterion.

**Stage 2: Position Estimation**
With 3 anchors, a node is able to triangulate its own position using least-squares (LS) algorithm. The LS algorithm is focused on minimizing the value of the objective function given by:

$$f(x) = \sum_{i=1}^{N} \left( \sqrt{(x-x_i)^2 + (y-y_i)^2} - d_i \right)^2$$

(3)

where \((x_i, y_i)\) are the coordinates of the \(i^{th}\) anchor and \((x, y)\) is the coordinate of the node. The measured range between the anchors and the node is \(d_i\). Before the transition to anchor, the node’s position estimate has to go through a residual test which is given by the value of the objective function \(f(x)\) at the specific estimate. A high residual indicates a divergence of the LS algorithm. In many cases, the estimation process faces a geometrical problem known as collinear anchor problem, where the three anchors are aligned in a straight line [12]. The result is the existence of two solutions to the minimization of the objective function. Therefore, if a node fails the residual test, it pulls out and tries to estimate its position later. In time, more nodes will become anchors and that node will have a better chance of passing the residual test and moving on to estimate its own position and upgrading to anchor.

**Stage 3: Anchor Nomination**
After passing the residual test and triangulating their own position, the nodes compute their QoE and enter into a transition state called anchor nominee where they have to compete with other neighboring nominees. If it has the best QoE then it establishes itself as an anchor. If it receives better QoE, on the other hand, then it goes back to node mode and attempts this procedure yet another time. In the cases that there are several nominees with the same best QoE, then they all become anchors. In actual implementation a spanning tree technique should be used to avoid unnecessary flooding of the network. Only new information triggers a broadcast, i.e. when a nominee receives better QoE information.

**Stage 4: New Anchors Incorporation**
All the nodes that had the chance to upgrade to anchors join the pool of other anchors in helping the remaining nodes to estimate their positions. The newly elected anchors start broadcasting their position and their own QoE index to the entire network. Eventually all the nodes end up in this stage where they have estimated their position with great accuracy.

In essence the contribution in CLOQ is based on two geometrical problems: collinear anchor problem and collinear node problem.
different criteria. The first is selecting the best anchors for triangulation and producing optimal QoE. The second is converting nodes to anchors according to a nomination process that elects the best QoE available at that iteration. As such the algorithm allows for minimizing of error propagation at each iteration while expanding the coverage of the ad-hoc sensor network safely.

IV. SIMULATION

In this section an outline of the simulation is followed by simulation results, where the accuracy of CLOQ performance will be highlighted.

A. Simulation Scenario

The simulation scenario is designed for outdoor-indoor applications similar to a military or fire fighter operation. The original reference points or anchors are placed outside the building, while sensor nodes are scattered indoors. The simulation is performed in 2-dimensional basis. The outside anchors have knowledge of their position a priori. In this simulation, a fixed amount of 4 reference points are used, while varying the other parameters such as the size of the building (Area I & II) and the number of nodes (node density). Node density is defined as the node/area. It is a measure of connectivity between the sensor nodes in an ad-hoc environment. Usually the higher the node density, the higher the connectivity and the position algorithm performs better. Table 2 outlines the simulation parameters.

The building blocks of the simulation are the PL and DME models introduced earlier in the paper. For each run of the simulation a number of sensor nodes are uniformly distributed in an area. The distance between each node and anchor is calculated. The simulated power is then computed from the PL model which generates received first path power for each distance input. The power seen by each sensor node to any of the anchors is translated to a ranging error obtained from the DME model. The use of the modeling in CLOQ simulation provides realistic radio propagation that incorporates shadow fading.

In order to compare CLOQ’s performance, another non-channel algorithm is simulated. This algorithm selects anchors based on minimum TOA or minimum distance. A node will triangulate its position once it has range information to three other anchors. If it has more than three then it selects the ones with smallest TOA or distance. After triangulation it immediately becomes an anchor. This algorithm will be known as Cooperative Localization using Minimum Distance (CLMD). As such it doesn’t take the effects of the channel into consideration for the selection criteria outlined in CLOQ. CLMD, however, uses the same DME and PL models for simulation.

B. Simulation Results

Two statistical measures are used in this paper to compare the algorithms in different environments. Average position error (APE) provides a good indicator for the performance evaluation of positioning algorithms. In addition the CCDF of positioning errors provides a detailed insight into the quality of the final solution. Particularly the 90% CCDF position error (90% CPE) values provides a measure that 90% of the time the positioning error is below a certain value. These two parameters will be used to compare both CLOQ and CLMD while varying the node density and the simulation area. Figures 5 and 6 show the APE and the 90% CPE respectively.

As apparent from the figures, increasing the node density has significant effect on lower densities. After a certain density, the algorithms don’t respond to any further change. Also, increasing the size of the area, in general, decreases the overall performance. In effect the limit of the algorithms performance is a function of the area. Smaller areas will have better position estimates for the following reason. Since the initial anchors are outside the deployment area, a decrease in the area increases the coverage the initial nodes see. As a result, the first nodes triangulating their position will have less error when compared to larger areas where coverage is smaller.

Comparing CLOQ and CLMD, it is apparent from the figures that the discrimination based on QoL and QoE in

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Figure 5: Average Position Error

Figure 6: 90% CCDF Position Error
CLOQ improves the performance substantially. This highlights the importance of the channel and the anchor selection criteria. In particular, CLMD has position errors that are greater than 1 meter in 90% of the time. In contrast, CLOQ provides position errors that are less than 1 meter in 90% of the time. Even better for node densities higher than 0.04, 90% of the time the error is below 0.5 meters. This is the significant improvement that CLOQ offers which is highly lucrative for ad-hoc sensor positioning applications. Also, CLMD for the smaller area doesn’t show any correlation with node density; while in larger area it has stronger correlation with increase in node density. This is mainly because in larger areas, sensor nodes are spaced out and as the density increases, the node-anchor spacing decreases at significant rate and thus the error decreases. Eventually changes in node density don’t have additional impact on CLMD error in larger areas.

Finally, Figure 7 shows the CCDF of positioning errors for CLOQ and CLMD at 0.2 node/m². Notice how CLOQ provides substantially lower position errors when compared to the other algorithm. This further supports the fact that placing a control on the transition from nodes to anchors helps in reducing the positioning errors and limits the propagation of errors throughout the network. One important observation here is that in very few cases, the error in both algorithms tends to be very high. This is mainly due to position error amplification due to geometry of some of the nodes and anchors at triangulation. Further studies and simulations need to be conducted to eliminate bad geometries.

V. CONCLUSION AND FUTURE WORK

In this paper it was shown that the modeling of the DME and PL for indoor ad-hoc sensor positioning application is very essential for error analysis and algorithm development. Utilizing these modeling efforts to develop a propagation channel-aware positioning algorithm can provide remarkable enhancement on the accuracy of the final solution. As the results have clarified, CLOQ succeeds in providing accurate positioning. Increasing the area with fixed number of anchors degrades the overall solution quality. Increasing the node density in a given area improves the positioning but only to a certain extent, then further increases don’t provide much improvement. This means that if a limited number of nodes need to be deployed in a certain scenario, then the simulation results can outline the minimum number of nodes required to achieve certain accuracy.

Further research will include analyzing the effect of the geometry on the performance of the algorithms. In addition, further modeling for different building types and scenarios will provide for a variety of indoor ad-hoc sensor positioning applications. Finally, extension of CLOQ to an outdoor scenario would incorporate the channel modeling efforts in different outdoor environments. More specifically location of anchors that surround nodes as opposed to anchors deployed randomly within the node distribution would highlight the strength and shortcomings of the algorithms.

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