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The Impact of Node Reliability on Indoor Cooperative Positioning

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***Abstract*—When implementing cooperative positioning (CP), there are a number of challenges and issues including the high computation complexity, the high probability of encountering unreliable reference nodes and coordinate uncertainty, which may offset the benefit of CP. To address these challenges, we study the impact of node reliability and propose a cooperative positioning scheme that identifies unreliable reference nodes in the system and adaptively adjusts the scoring threshold based on the geographic locations of reference nodes. When compared with other three conventional cooperative positioning schemes, our simulation results indicate that the proposed scheme can achieve the best accuracy of about 2 meters within five iterations, and it is about 32% better than the conventional schemes in terms of accuracy.**

***Index Terms*—node reliability; cooperative positioning**

I. Introduction

Highly accurate and ubiquitous indoor positioning is a current hot research topic. Among all the indoor positioning methods based on wireless technologies such as Ultra Wide-band (UWB), WiFi and so on [1], WiFi is the most attractive one owing to the rapid widespread use of 802.11 embedded products and the continuously expanding WiFi coverage in public areas. Thanks to unified development platforms such as Brillo, the hot concept of Internet of Things (IoT) is spreading rapidly, and such trend offers a feasible platform for implementing a WiFi-based indoor positioning system [2]. Besides, WiFi can support high speed data transmission, so the transmission and overhead of positioning information is never a matter. In a WiFi-based positioning system, the nodes with known accurate coordinate information are called *anchors* while nodes with unknown coordinate information are *agents*. Depending on whether an agent takes part in the positioning process of other agents, we can divide positioning into non-cooperative positioning (nCP) and CP [3]–[5].

Benefit from WiFi products and wireless development platforms, it is now practical to support CP to enhance traditional nCP approaches. To adopt WiFi-based CP, several technical issues should be tackled to avoid accuracy degradation. They include the coordinate uncertainty, None-Line-Of-Sight (NLOS) signal propagation, multi-path problem, etc. In this paper, these problems are encapsulated in the node reliability problem and they may offset the benefit of CP. An important issue is to identify whether a set of reference nodes is reliable or not. In nCP, there are some criteria used to evaluate the positioning performance of a set of reference nodes like the Camer-Rao bound (CRB) [6], Geometric Dilution of Precision (GDOP) [7] and fitness function [8]. For example, CRB is utilized to predict a lower bound on the covariance of any unbiased location estimate. The CRBs for both received signal strength indicator (RSSI) and time of arrival (TOA) distance measurements are derived in [9], [10]. Some later works [11]–[13] apply this criterion to propose diverse selection algorithms. But these criteria do not take the uncertainty of agents into account. Therefore, these criteria are not suitable for CP reference node selection. To tackle the uncertainty problem, alternative solutions are investigated in the past few years. In [14], the modified bayesian Cramer-Rao bound (MBCRB) taking ranging quality, geometry and uncertainty into account is introduced, but the computational complexity is high. Another solution is Squared Position Error Bound (SPEB) [15], which was first proposed in [16], then authors of [15] derived it in a closed-form by considering the imperfect a priori location knowledge of the located agent. [15] also proposed a mobile terminal (MT) selection scheme. By combining SPEB and coalition formation games, a utility function is designed in [17], [18].

We focus on identifying the node reliability to select the optimal reference node set for agent to be located and propose a reliability-based CP scheme with combined techniques. The major contributions of this paper are as follows:

1) We design a set of criteria for reference node reliability evaluation so that unreliable reference nodes in the system can be readily identified.
2) We propose a reference node prioritization scheme with low computation cost at agents. The SPEB [15] and the proposed orientation index are used to estimate the positioning performance and hence facilitate the reference node selection process.
3) The proposed scheme and three conventional positioning schemes are implemented and simulation is conducted to evaluate the performance of the proposed scheme.

The reminder of this paper is organized as follows. The methodologies exploited in this paper are introduced in Section II. In Section III, the proposed scheme is discussed in detail. After that, Section IV presents the simulation results and the corresponding analysis. Finally, Section V concludes the paper.

II. Methodologies

A. RSSI-based distance estimation

In terms of distance estimation, we apply the path loss model for wireless radios in [19] as follows.

$$P_r(d) = P_0(d_0) - 10\gamma \log_{10} \frac{d}{d_0} + X_\sigma \quad (1)$$

where $P_r(d)$ is the received power with distance d and $P_0(d_0)$ represents the received power at the reference distance d_0. Besides, γ denotes the path loss exponent, X_σ is a log-normal random variable with variance σ^2. If we ignore X_σ, (1) can be used to calculate the distance d for the target.

$$d = d_0 10^{\frac{P_0(d_0)-P_r(d)}{10\gamma}} \quad (2)$$

However, the practical indoor environment is more complicated because of NLOS, multi-path and so on. These problems lead to large errors and the reference nodes with such kind of issues are considered to be "unreliable". We assume the distribution of unreliable reference node with large errors and the corresponding error follow Gaussian distribution with zero mean, and we call it the calibration standard deviation. According to our empirical measurements, we found the average calibration standard deviation $\sigma_C = 2.12$ dB and the average RSSI standard deviation $\sigma_{RSSI} = 1.49$ dB.

B. SPEB and Reference node orientation index

The SPEB offers a lower bound to characterize the localization accuracy of an agent with unknown location. As mentioned, authors in [15] take the anchor uncertainty into account and derive a closed-form SPEB according to RSSI-based distance measurement. This paper utilizes (3) to estimate the positioning variance of an agent.

$$\mathcal{P} = \frac{\sum_{n=1}^{N} \frac{1}{\beta_n}}{(\sum_{n=1}^{N} \frac{\cos^2\phi_n}{\beta_n})(\sum_{n=1}^{N} \frac{\sin^2\phi_n}{\beta_n}) - (\sum_{n=1}^{N} \frac{\sin\phi_n \cos\phi_n}{\beta_n})^2} \quad (3)$$

where $\beta_n = \omega_n^2 + \varepsilon^2 d_n^2$, and $\varepsilon = \frac{\sigma \ln 10}{10\gamma}$. Here d_n denotes the distance from the reference node to the agent to be located. σ is the shadowing standard deviation. ω_n^2 denotes the variance of a priori knowledge of the n-th located reference node (for an anchor, $\omega_n^2 = 0$). The last symbol ϕ_n denotes the angle from the n-th reference node to the un-located agent.

Orientation index, is utilized in this paper to assist the estimation of SPEB. For the situation with N reference nodes and one un-located agent, if the agent is connected to each reference nodes with lines and no three nodes lie on a straight line, there are N angles θ formed by these straight lines. The reference node orientation index can be calculated as follows.

$$\mathcal{V}_N = \frac{1}{N}\sum_{n=1}^{N}(\theta_n - \frac{2\pi}{N})^2 \quad (4)$$

The index reflects how uniform the reference nodes are distributed with respect to the target agent. The smaller the index, the better the positioning performance.

III. The Proposed Scheme

The proposed scheme can be divided into two stages: the off-line stage and on-line stage.

A. System model

We focus on addressing the two dimensional localization problem, the system model consists of N anchors and M agents. N anchors that offer accurate coordinate information and adaptive threshold t_a construct the set $\mathcal{N}$. For an arbitrary node i, it can discover a set of anchors $\mathcal{N}_{\to i}$. Similarly, we have the agent sets $\mathcal{M}$ and $\mathcal{M}_{\to i}$ with unknown coordinates or localization uncertainty. We define the combination of $\mathcal{N}$ and $\mathcal{M}$ to be $\mathcal{S}$. And $\mathcal{C}_{\to i}$, which is composed of $\mathcal{N}_{\to i}$ and $\mathcal{M}_{\to i}$, denotes the set of reference nodes that node i can detect.

B. The off-line stage

The first stage is to figure out the parameters in (1) for a certain environment. More specifically, at the off-line stage, each node collects the RSSI values from other nodes. Then with the assumption that all the connections share the same transmit power, path loss factor, shadowing standard deviation, the parameters in RSSI-to-distance transformation can be calculated with curve fitting. After that, the RSSI-based distance estimation can be executed in the on-line stage.

C. The on-line stage

The on-line stage can be divided into the unreliable reference node recognition, orientation index threshold adaptation and positioning phases.

1) The positioning phase: In this phase, each agent will first discover nodes within its sensing range $\mathcal{C}_{\to i}$ combined of neighboring anchors $\mathcal{N}_{\to i}$ and agents $\mathcal{M}_{\to i}$ and collect the available localization information. In addition, RSSI values are transformed to distance values. For each $\mathcal{C}_{\to i}$, we suppose the number of anchors in $\mathcal{N}_{\to i}$ is n and the number of agents in $\mathcal{M}_{\to i}$ is m. The next step is to sort the reference node queue. Each agent i has a vector composed of distances between itself to all reference nodes. Then for distance $d(i,j)$ measured from node j, it would be multiplied by two coefficients: w_t and w_r. Specifically, $w_t = w_{t1} = 1$ if node j is an anchor and $w_t = w_{t2} = 1.5$ if node j is an agent. If node j is not included in the unreliable reference node list, $w_r = w_{r1} = 1$. Otherwise, $w_r = w_{r2} = 1.9$ if node j is an anchor and $w_r = w_{r3} = 1.4$ if node j is an agent. We then have a new vector, and elements in this vector are the criteria for the corresponding reference nodes. A smaller $w_t * w_r * d(i,j)$ indicates a higher priority in the reference node set. Then we sort the criteria vector, and with the same order, we establish the corresponding reference node queue $\mathcal{L}$. According to $\mathcal{L}$, all available reference nodes are merged into the reference node set one by one. Each time the new coordinates are calculated, the corresponding orientation index $V_a(\mathcal{R})$ and SPEB $\mathcal{P}(\mathcal{R})$, are computed as well. Once $V_a(\mathcal{R})$ reaches the threshold t_a, the process terminates and the current reference node set is adopted. Otherwise, based on the merge and split rules in [20], node j will be removed from or added to the reference node set. Algorithm 1 illustrates the positioning phase.

Algorithm 1 Pseudocode for the positioning phase (executed by agents)

for all agent $i \in \mathcal{M}$ **do**
  discover $\mathcal{N}_{\to i}$, $\mathcal{M}_{\to i}$ and $\mathcal{C}_{\to i}$
  collect localization information from $\mathcal{C}_{\to i}$
  calculate distance $d(i, j \in \mathcal{C}_{\to i})$ based on RSSI
  calculate $l_{i,j} = w_t * w_r * d(i,j)$ and queue $\mathcal{L}$
  select three reference nodes with minimum l to form $\mathcal{R}$
  utilize $\mathcal{R}$ to calculate coordinates, the corresponding orientation index $V_a(\mathcal{R})$ and SPEB $\mathcal{P}(\mathcal{R})$
  for $j = 4$:size of $\mathcal{L}$ **do**
    if $V_a(\mathcal{R}) < t_a$ **then**
      break
    end if
    add node k with the j-th minimum l to set $\mathcal{R}$
    utilize $\mathcal{R}$ to calculate $V_a(\mathcal{R})$ and $\mathcal{P}(\mathcal{R})$
    if $\mathcal{P}(\mathcal{R}) > \mathcal{P}(\mathcal{R} - node_k)$ **then**
      remove node k from $\mathcal{R}$
    end if
  end for
  utilize $\mathcal{R}$ to be the reference node set and calculate coordinates for agent i
end for

2) *The unreliable reference node recognition phase:* In this phase, after collecting available positioning information from neighboring nodes, each anchor calculates its distances to other reference nodes with coordinate information, then the calculated distances are transformed to RSSIs and compared with the measured RSSIs. Ideally, the difference between the calculated RSSIs and the measured RSSIs should be zero, but it is hard to achieve in reality. The algorithm first remove a reference node from the set, then the average RSSI error of the remaining reference nodes is calculated, which denotes the reliability score of the removed node. Consequently, by removing reference nodes one by one, the corresponding reliability scores of all reference nodes can be figured out. For more reliable nodes, their scores are higher. In our algorithm, we denote the worst 20% reference nodes as unreliable reference nodes. The unreliable reference node list is then broadcasted to other nodes for them to conduct the orientation index threshold adaptation phase as well as the positioning phase. Algorithm 2 describes the unreliable reference node recognition phase.

3) *The orientation index threshold adaptation phase:* Similar to Algorithm 1, each anchor first calculates its coordinates based on a set of reference nodes. The difference is that the merge and split rules depend on the actual positioning error $E(\mathcal{R})$ instead of SPEB $\mathcal{P}(\mathcal{R})$, and all the available reference nodes are estimated in this process. Each anchor has a set of reference nodes and the corresponding orientation index $V_a(\mathcal{R})$. They communicate and compute the average value of their orientation indexes to be the initial threshold t_a. In order to improve the threshold t_a, anchors cooperate with each other to adjust it iteratively. In each iteration, anchors apply Algorithm 1 and calculate the actual mean positioning errors

Algorithm 2 Pseudocode for the unreliable reference node recognition phase (executed by anchors)

for all anchor $i \in \mathcal{N}$ **do**
  discover $\mathcal{N}_{\to i}$, $\mathcal{M}_{\to i}$ and $\mathcal{C}_{\to i}$
  collect localization information from $\mathcal{C}_{\to i}$
  calculate the distance matrix with coordinate information and transform it to RSSI matrix
  calculate the difference matrix with calculated RSSI matrix and measured RSSI matrix
  for $j \in \mathcal{C}_{\to i}$ **do**
    calculate the corresponding reliability score
  end for
  select 20% reference nodes with the worst scores as unreliable reference nodes
end for

with three different thresholds, t_a, $t_a * \delta_s$ and t_a/δ_s, where the step size δ_s is an arbitrary constant. The threshold is then updated iteratively until no smaller error can be achieved, and the maximum number of iterations is 10 in our simulation. Consequently, the final threshold is figured out and broadcasted to agents to execute the positioning phase. Algorithm 3 illustrates the orientation index threshold adaptation phase.

IV. Simulation And Experimental Results

A. Simulation Setup and Positioning performance criteria

We consider a 21×21 m^2 area, multiple anchors are placed regularly while multiple agents are placed randomly. The two significant parameters γ and σ for SEPB calculation are fixed to be 2.77 and 4.4 dB respectively. $\delta_s = 1.5$ and $iter_{max} = 10$. Besides, noise in the simulation follows two kinds of distribution. The first is white Gaussian noise with zero mean and different standard deviations. The other type of noise contains the calibration standard deviation. Two basic sets of noise distributions are $\sigma_C = 0$ dB, $\sigma_{RSSI} = 3.2$ dB and $\sigma_C = 2.12$ dB, $\sigma_{RSSI} = 1.49$ dB. Three conventional algorithms, including the MT [15], selection scheme based on utility function and gridiron spatial correlation (UF-GSC) [17] [21] and links selection strategy inspired by mono-objective genetic algorithm (MGA) [13], are simulated as benchmarks. The program runs 100 times on MATLAB for every set of configuration. The performance of a positioning system is evaluated from three aspects: mean positioning error, complementary cumulative distribution function (CCDF) of the positioning error and the convergence speed. The CCDF data are collected at the tenth iteration.

B. Simulation Results and Analysis

We set both the number of anchors and the number of agents to be 25, and based on two basic sets of noise configurations, we have two sets of results as shown in Fig. 1 to 4. Overall, the proposed scheme provides better performance compared with the other three conventional algorithms. The mean positioning errors are within 1.4 meters after the first iteration. The proposed scheme provides at least 53% improvement compared

Algorithm 3 Pseudocode for the orientation index threshold adaptation phase (executed by anchors)

Initialize stepsize δ_s and maximum iteration time $iter_{max}$;
for all anchor $i \in \mathcal{N}$ **do**
  discover $\mathcal{N}_{\to i}$, $\mathcal{M}_{\to i}$ and $\mathcal{C}_{\to i}$
  collect localization information from $\mathcal{C}_{\to i}$
  calculate distance $d(i, j \in \mathcal{C}_{\to i})$ based on RSSI
  calculate $l_{i,j} = w_t * w_r * d(i,j)$ and queue $\mathcal{L}$
  select three reference nodes with minimum l to form $\mathcal{R}$
  utilize $\mathcal{R}$ to calculate the estimated coordinates
  utilize the actual and estimated coordinates to calculate positioning error $E(\mathcal{R})$, namely d(actual location, estimated location), and orientation index $V_a(\mathcal{R})$
  for $j = 4$:size of $\mathcal{L}$ **do**
    add node k with the j-th minimum l to set $\mathcal{R}$
    utilize $\mathcal{R}$ to calculate $E(\mathcal{R})$ and $V_a(\mathcal{R})$
    if $E(\mathcal{R}) > E(\mathcal{R} - node_k)$ **then**
      remove node k from $\mathcal{R}$
    end if
  end for
  utilize $\mathcal{R}$ to be the reference node set and calculate $V_a(\mathcal{R})$ for anchor i
end for
calculate the average orientation index to be the initial value of adaptive threshold t_a
for $i = 1 : iter_{max}$ **do**
  with threshold t_a, $t_a * \delta_s$ and t_a/δ_s, all anchors apply the same positioning algorithm as agents to calculate the actual mean error $E(t_a)$, $E(t_a * \delta_s)$ and $E(t_a/\delta_s)$
  modify t_a to the one with the smallest actual mean error
end for

with other algorithms. The worst improvement occurs at the scenario with the white Gaussian noise and the second best algorithm is MT. By referring to the CCDF, in the worst case, the proposed scheme can guarantee 2 meters accuracy for 80% of the agents. Besides, Fig. 1 and 3 show that the proposed scheme can converge within five iterations.

In the next simulation, both the number of anchors and the number of agents are 25. We multiply the two basic sets of noise parameters by coefficients ranging from 0.5 to 2.5 with 0.5 interval. The corresponding results are demonstrated in Fig. 5 and 6. When the coefficient is equal to 0.5, the difference in error among these algorithms are small. As the noise coefficient increases, the gap of mean positioning error among these algorithms changes as well. But the proposed scheme can maintain at least 32% enhancement compared with the second best algorithm.

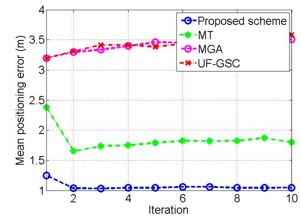

Fig. 1. Mean positioning error with 25 anchors, 25 agents, $\sigma_C = 2.12$ dB and $\sigma_{RSSI} = 1.49$ dB.

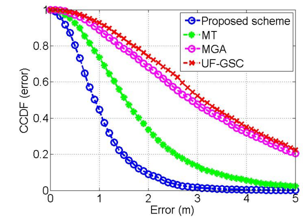

Fig. 2. CCDF with 25 anchors, 25 agents, $\sigma_C = 2.12$ dB and $\sigma_{RSSI} = 1.49$ dB.

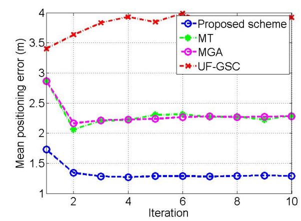

Fig. 3. Mean positioning error with 25 anchors, 25 agents, $\sigma_{RSSI} = 3.2$ dB.

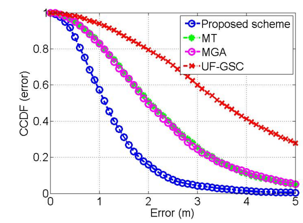

Fig. 4. CCDF with 25 anchors, 25 agents, $\sigma_{RSSI} = 3.2$ dB.

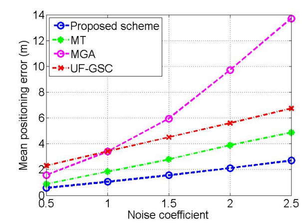

Fig. 5. Mean positioning error under different noise (with σ_C).

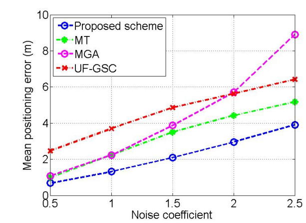

Fig. 6. Mean positioning error under different noise (without σ_C).

V. Conclusion

Indoor WiFi-based CP is motivated by the rapidly growing population of WiFi users and hotspots. To tackle the practical challenges and problems of CP implementation such as the coordinate uncertainty introduced by agents, we have studied the impact of node reliability and proposed a reliability-based CP scheme in this paper. Specifically, we have designed the unreliable reference node recognition algorithm that the anchors are exploited to identify abnormal nodes in the system. Based on distance, geometry and reference node uncertainty, we have further proposed a reference node prioritization scheme, in which the queue sorting and scoring threshold adaptation techniques are exploited to facilitate the reference node selection and reduce the computation cost in agents. In general, the proposed scheme can achieve an accuracy of about 2 meters according to our simulation results. Three other conventional positioning algorithms are also simulated as benchmarks. When compared with them, the proposed scheme is at least 32% better in terms of positioning accuracy.

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