Distributed localization using mobile beacons in wireless sensor networks

Abstract A new distributed node localization algorithm named mobile beacons-improved particle filter (MB-IPF) was proposed. In the algorithm, the mobile nodes equipped with globe position system (GPS) move around in the wireless sensor network (WSN) field based on the Gauss-Markov mobility model, and periodically broadcast the beacon messages. Each unknown node estimates its location in a fully distributed mode based on the received mobile beacons. The localization algorithm is based on the IPF and several refinements, including the proposed weighted centroid algorithm, the residual resampling algorithm, and the markov chain monte carlo (MCMC) method etc., which were also introduced for performance improvement. The simulation results show that our proposed algorithm is efficient for most applications.

Keywords wireless sensor network, node localization, mobile beacons, MB-IPF algorithm

1 Introduction

WSN is an emerging technology for monitoring the physical world with a densely deployed network of sensor nodes. It can be used in a variety of applications such as environment monitoring, military surveillance, etc [1]. Node self localization is a fundamental problem in WSN e.g. sensor nodes have to be aware of their locations to be able to specify the place where an event takes place [2]. Also, the routing efficiency for several cluster-based routing algorithms such as in Refs. [3–4] can be improved if the sensors know their positions. However, it is an infeasible solution if all the nodes equip with a GPS considering the costs and the energy factors. It is also unlikely that the position of each node can be predetermined by a network of thousands of nodes.

The existing node localization algorithms can be divided into centralized algorithms, which collect measurements at a central processor prior to calculation, and distributed algorithms, which require sensors to share information only with their neighbors, but possibly iteratively [5]. The main centralized algorithms include maximum likelihood estimation [6], convex optimization method [7], a distributed semi-definite programs (SDP-based) localization algorithm [8], multidimensional scaling (MDS) algorithms [9], etc. The main distributed algorithms include two categories: network multilateration [10–11] and successive refinement [12–13].

Now, some researches target the case where some nodes can move in WSN. Node localization with mobile nodes was first considered in Ref. [14]; the present researches study how mobility makes localization more difficult. In Ref. [15], the authors use the geometry method to determine the sensor node’s location based on the cross point of the two chords in a circle. Hu et al. used the sequential Monte Carlo method for the mobile node localization [16].

In this article, we mainly focus on the node localization assisted by the mobile beacons, and propose a localization algorithm named MB-IPF to estimate the unknown nodes’ locations. In the localization system, the mobile nodes move around in the WSN field based on the Gauss-Markov mobility model, and broadcast the beacons and sound energy periodically. All the other static unknown nodes estimate their locations using the received beacons in their sensing range. Various improved methods were also used to increase the localization accuracy e.g. the Weighted Centroid algorithm was introduced to obtain the initial estimation point, data filtering methods were used to select the optimal localization beacons, the residual resampling algorithm and the MCMC method were used to solve the sample depletion phenomenon. The simulation results show that the proposed node localization method is efficient.

2 MB-IPF localization model

2.1 MB-IPF localization methodology

The WSN presented is composed of two different types of
nodes: static sensors and mobile sensors. Figure 1 illustrates the localization environment. The triangles denote the beacons received by the static unknown node; the curves denote the mobility trajectories of the mobile nodes; the big circle denotes the sensing range of a static node. During the localization process, each unknown node receives the beacon packets within its sensing range and records its position and energy information. The unknown nodes estimate their own locations by solving the associated state evolution and the observation model based on the received beacon packet sets.

2.2 Mobile node trajectory

To localize all the unknown nodes in the sensor field, it is necessary to determine the optimum trajectory and the optimum broadcasting time of the beacon packets. However, the problem is quite complicated since the positions of the unknown nodes are not known a priori. In the robot localization, the robot can traverse the field along the predefined trajectory maps. However, there are substantial differences between the robot localization and the node localization for WSN because each mobile node has little or no control of its mobility. Here, to cover every unknown node, the Gauss-Markov mobility model [17] was adopted for the mobile nodes. The model can be presented by:

\[ v_i = \alpha v_{i-1} + (1-\alpha) \nu + \rho_1 \sqrt{1-\alpha^2} \]  
\[ d_i = \alpha d_{i-1} + (1-\alpha) \vartheta + \rho_2 \sqrt{1-\alpha^2} \]

where \( v_i \) and \( d_i \) are the new speed and direction of the mobile node at time interval \( k \); \( \rho_1 \) and \( \rho_2 \) are random variables from a Gaussian distribution; \( \alpha (0 \leq \alpha \leq 1) \) is the tuning parameter used to vary the randomness; \( \nu \) and \( \vartheta \) are constants representing the mean value of speed and direction as \( k \rightarrow \infty \).

At each time interval, the next location is calculated based on the current location, speed, and direction of movement, and the position is given by:

\[ x_k = x_{k-1} + v_{k-1} \cos d_{k-1} \]  
\[ y_k = y_{k-1} + v_{k-1} \sin d_{k-1} \]

where \((x_k, y_k)\) is the mobile node's position at \( k \) time.

2.3 MB-IPF localization model

The state-space dynamic model of the node localization in the WSN can be expressed as follows:

1) Unknown node state model

According to the localization method described above, the position of the unknown node remains unchanged after deployment, that is, the state dynamics governing the unknown node's position is simply the identity function:

\[ X_k = X_{k-1} + w_k \]

where \( X_k = [x_k, y_k]^T \) denotes the position of an unknown node, and \( w_k \) denotes the small position perturbation owing to wind or other environmental effects.

2) Unknown node measurement model

When sound is propagating through air, it is known that the acoustic energy is emitted omni-directionally from a point source. Assuming that the sound propagation is lossless, the energy measurement \( z_k \) is related to the beacon's position \( \zeta_k \) as:

\[ z_k = \frac{S}{\| X_k - \zeta_k \|^2} + n_k \]

where \( S \) is the energy of the sound source, \( \beta \) is the attenuation parameter, \( n_k \) models the observation error, which usually occurs owing to the environmental effects, and we assume \( n_k \sim N(0, \sigma^2) \).

Based on the localization model, each unknown node uses the proposed MB-IPF algorithm to estimate its location. We summarize the whole algorithm in the following section.

3 MB-IPF localization algorithm

The whole proposed distributed localization algorithm consists of three main phases:

1) Information sampling and filtering phase;
2) Initial point estimation phase;
3) Self-localization phase. Prior to elaborating on the whole algorithm, we first introduce some improved methods to
increase the accuracy and reduce the computation burden.

3.1 Data filtering for localization

The raw data collected from the mobile nodes are noisy; it is necessary to filter them before localization: Using the beacons whose energy signal has higher SNRs; discard the beacon whose value $\mathbf{z}_i$ in $\mathbf{z} = (\mathbf{z}_1, \ldots, \mathbf{z}_n)$.

Triangular inequality judgement rule: if the unknown node $C$ receives two beacons $A$ and $B$, the range information should have $d(A, B) = d(A, C) + d(B, C)$.

If such a relationship does not hold good, the current received beacons are ignored. Using these simple filtering techniques, we can obtain the reliable beacons for localization.

3.2 Weighted centroid algorithm

The initial point is very important for the iterative algorithms. Hence, it is crucial to determine the closest initial point to the true location. Inspired by Ref. [18], we also introduce the centroid technique to obtain it. Given the locations of $m (\geq 3)$ beacons $(\mathbf{x}_1, \ldots, \mathbf{x}_m)$ and the corresponding sensing data $(\mathbf{z}_1, \ldots, \mathbf{z}_n)$ from the mobile node, the location of each unknown node in a plane can be approximately estimated as a weighted centroid of its filtering beacons’ locations. Each weight $(w_1, \ldots, w_m)$ disregarding the noise is expressed by:

$$w_1 \ldots w_m = z_1 \ldots z_n = \| \mathbf{x}_0 - \mathbf{z}_1 \|^2 \ldots \| \mathbf{x}_0 - \mathbf{z}_n \|^2$$

The unknown node’s location $\mathbf{X}_0$ is given by:

$$\sum_{i=1}^{m} w_i \mathbf{z}_i / \sum_{i=1}^{m} w_i.$$  \(7\)

We use the $\mathbf{X}_0$ as the initial estimation point in our MB-IPF algorithm.

3.3 MB-IPF localization algorithm

Owing to the nonlinearity of Eq. (6), the improved PF was proposed to solve the generalized non-linear or non-Gaussian sequential estimation using sequential Monte-Carlo simulation. Apart from the two improved methods described above, we also introduce some other improved techniques into the node localization including:

1) Information sampling
   a) The mobile nodes start to move in the field based on the Gauss-Markov model, and broadcast the beacons and acoustic signal periodically;
   b) Each unknown node in its sensing range receives the beacons and acoustic energy, and records $[\mathbf{r}, \mathbf{z}]$ in its information set;
   c) The beacons are filtered according to the methods described in Sect. 3.1.

2) Initial point estimation
   After receiving $m$ beacons, the weighted centroid point can be estimated as: $\mathbf{X}_0 = \sum_{i=1}^{m} w_i \mathbf{z}_i / \sum_{i=1}^{m} w_i$, which is described in Sect. 3.2.

3) Self localization
   a) Initialization $k=0$: draw $N$ particles from the initial positions $\mathbf{X}_0$ from prior position $\mathbf{X}_0$, and the initial weight is $1/N$;
   b) For $k=1, 2, \ldots$
      a) Importance sampling:
         i. Sample $N$ particles from the $\mathbf{X}_i \sim p(\mathbf{X}_i | \mathbf{X}_{i-1})$.
         $\mathbf{x}_i = \mathbf{x}_{i-1} + \mathbf{w}_i \mathbf{z}_i$, $\mathbf{y}_i = \mathbf{x}_i + \mathbf{w}_i \mathbf{z}_i$, $i = 1, 2, \ldots, N$ of the unknown node position;
      ii. Calculate weights by:
         $\omega_i = \omega_{i-1} e^{(\mathbf{z}_i - \mathbf{x}_i)^T/(2\sigma^2)}$;
      iii. Normalize the weights by:
         $\hat{\omega}_i = \omega_i / \sum_{i=1}^{N} \omega_i$;
      iv. Resample: Calculate the valid particles: $N_{eff} = 1/\sum_{i=1}^{N} \hat{\omega}_i^2$; If $N_{eff} < \eta N$, 0 < $\eta < 1$, then, perform the residual resampling to obtain $N$ random samples $\mathbf{X}_{0,i}$ approximately distributed according to $p(\mathbf{X}_{0,i} | \mathbf{z}_i)$, and set $\omega_i = \hat{\omega}_i = 1/N$ for all $i$.
   c) MCMC method: adopt the MH algorithm in the MCMC method to artificially move the particles;
   d) Estimate the unknown node’s location: the node’s location can be determined using the particles and the corresponding weights $\omega_i$: $\hat{x}_i = \sum_{i=1}^{N} \omega_i \mathbf{x}_i$, $\hat{y}_i = \sum_{i=1}^{N} \omega_i \mathbf{y}_i$.
   e) Residual unknown nodes localization
      The unknown nodes that have been localized become new actual anchors. The residual nodes use these new anchors to estimate locations.
4 Simulation results

4.1 Simulation scenario

Extensive simulations have been conducted to evaluate the performance of the proposed algorithm. For all simulations, 100 sensor nodes are randomly distributed in a 1x1 km rectangular region. We assume that: every unknown node’s sensing range $r$ is fixed at 60 m, and that each node can receive the beacons reliably within 52 m; the sound source energy $S=5\,000$, and the noise level satisfies the normal distribution; the variance of the Gaussian measurement noise is set as $1e-5$; the speed of the mobile node is fixed at 8 m/s, the value of $\vec{d}$ is initially 90 degrees but changes over time according to the edge proximity of the node; $\rho_s$ and $\rho_d$ are random variables from a Gaussian distribution, the tuning parameter $\alpha=0.75$; the broadcasting interval is 2 s; the number of particles is set as $N=1\,000$, and the number of times of Monte Carlo run is 25.

4.2 Performance evaluation

In the sensor node localization, we generally consider three performance metrics: computation overhead, communication overhead, and accuracy. In the proposed MB-IPF algorithm, each unknown node estimates its position respectively, and therefore, its computation complexity is $O(n)$ ($n$ is the number of the nodes for localization). During the localization process, each unknown node only passively receives the beacons from the mobile node, and it requires no inter-sensor or sensor-to-mobile node communication apart from the residual unknown node localization phase. This is one major advantage of the proposed algorithm because the communication is generally more energy-consuming than the computation. In the following subsections, we mainly focus on the accuracy of the proposed localization algorithm.

1) Mobile node mobility trajectory and beacons

Figure 2 shows a trajectory based on the Gauss-Markov mobility model within the WSN field. The dotted circle indicates the sensing range of a representative unknown node. Along the trajectory, the mobile node broadcasts beacon packets periodically. As seen in Fig. 2, the trajectory can cover almost the entire sensor field. Thus, the Gauss-Markov mobility model is suitable for the node localization system.

Figure 3 shows the beacons clearly along the trajectory in a representative unknown node’s valid sensing range. The stars indicate the received beacons. The number beside the star indicates the sequence. Figure 3 shows that the representative unknown node received 22 beacons at current time.

2) Localization results using different initial estimation point

The initial estimation point is very important for the iterative estimation. Here, we compare the localization results using the closest point approach (CPA) initial point and the weighted centroid initial point. We denote the plots as CPA start and the Weighted Centroid start, respectively. As seen in Fig. 4, the latter performs quite well for small numbers of beacons. This is the expected result and it proves that the weighted centroid initial point is essential in the MB-IPF algorithm.
3) Localization accuracy comparison using different localization algorithm

To compare the localization accuracy, we also performed the weighted mean algorithm and the centroid algorithm in our simulations. The weighted mean algorithm takes the acoustic signal strength weighted mean of the received beacons’ locations as the estimated unknown location:

\[ X_{\text{weighted-mean}} = \frac{\sum_{i=1}^{k} z_i c_i}{\sum_{i=1}^{k} c_i} \]

The centroid algorithm takes the mean of the received beacons’ locations as the estimated unknown location:

\[ X_{\text{centroid}} = \frac{1}{k} \sum_{i=1}^{k} z_i \]

Figure 5 shows the estimation tendency of a representative unknown node to its true location in one simulation; the final estimation location using MB-IPF is very close to the true node. As seen in Fig. 5, the MB-IPF demonstrates superior performance among the three localization algorithms.

The average localization error using the MB-IPF, the weighted mean algorithm, and the centroid algorithm, respectively, can be seen from Fig. 6. The estimation error decreases with increasing beacons. The MB-IPF demonstrates superior performance. Its average localization error is less than 5 meters, whereas the average error is about 10 meters using the weighted mean algorithm and the centroid algorithm. The weighted mean algorithm has higher localization accuracy when compared with the centroid algorithm.

Apparently, increasing the mobile nodes or the frequency of the beacons’ announcements will increase the localization accuracy, but it also increases the computation burden. However, increasing the beacons does not always produce better results when the error enters steady state behavior with unpredictable fluctuations. The tradeoff must be considered.

5 Conclusions

1) The MB-IPF algorithm is novel. The “virtual” beacons eliminate the need to deploy the actual stationary anchors. The adopted Gauss-Markov mobility model is suitable for the current node localization system.

2) The MB-IPF algorithm is very accurate: The acoustic energy model has higher accuracy for ranging. The algorithm based on PF effectively solved the non-linear and non-Gaussian problem of the observer model. The refinements such as the proposed weighted centroid, the residual resampling algorithm, and the MCMC method etc., improved the localization performance.

3) There is no sensor-to-mobile node or inter-sensor communication except for the residual unknown node localization phase, which leads to save considerably more energy.

4) The MB-IPF algorithm is robust and scalable. Each static node runs the algorithm in fully-distributed mode allowing high scalability to large WSN. It is robust with failure loss of nodes.

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References


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