A Survey on Cooperative Localization in Wireless Sensor Network

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Abstract

Localization technology in Wireless Sensor Network (WSN), which can obtain location information of node data sources, is considered to be one of the key technologies. Therefore, WSN is widely used in military, commercial and public services and other aspects. Traditional positioning technique, which requires a large number of anchor nodes to be deployed, that is, through the anchor nodes with Global Position System (GPS) location information, to locate the agent nodes without location information accurately. However, extensive deployment of anchor nodes is expensive. In this case, there are many researchers who have done tremendous research on this problem in recent years, and proposed Cooperative Localization, which utilizes the communication between target nodes to assist in positioning. This paper makes a detailed investigation on the cooperative positioning technology, analyzes and discusses the hot and difficult problems of the current research, and points out the future development direction and application prospect.

Keywords

Wireless Sensor Network,Localization Technology,Cooperative Localization.

1. Introduction

Wireless Sensor Network (WSN), which contains many sensor nodes with low cost, low power consumption and other characteristics, is a self-organizing network [1], so WSN is widely used in environmental monitoring , location tracking and other fields [2-3]. As a key technology in WSN, many scholars have done a lot of researches on node location. In recent years, Chowdhury et al. made a detailed review for positioning technology research [4].

Nodes localization technology can be divided into two categories: cooperative localization and non-cooperative localization. In non-cooperative localization, agent nodes can only receive information from anchor nodes within their communication radius, and then are located by acquiring information from multiple anchor nodes. In cooperative localization, agent nodes can not only receive anchor nodes information in its communication radius, but also exchange information with other agent nodes to assist positioning (Fig. 1), and its positioning accuracy is higher than non-cooperative localization [4].

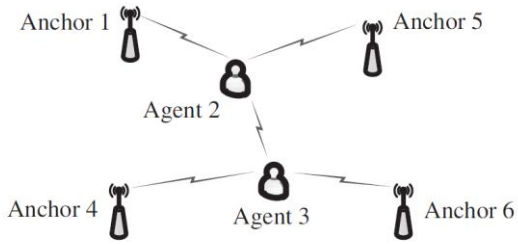

Fig.1 Digram of cooperative localization

In 1990s, Japanese scholar Kurazume Ryo et al. proposed the concept of cooperative localization in the study of multi-robot positioning for the first time [5]. In recent years, localization and navigation technology in many applications are playing an increasingly important role, while location-based services also contains a huge commercial value [6]. As one of the most promising research areas in the field of localization and navigation [7], cooperative localization is becoming universal in the study of multi-robot localization, wireless sensor network localization, wireless mobile network localization, underwater autonomous aircraft localization and satellite localization. A new research topic have been drawn much attention by the academic community and the industry.

2. Cooperative Localization

2.1 Genre of Cooperative Localization

Cooperative localization has a wide range of applications, free from time and space constraints, with good dynamic adaptability. Even in the case of unknown geographical information, it can also achieve precise positioning through the interaction between users.

Cooperative localization algorithm can be divided into Bayesian-based method and non- Bayesian-based method (Fig. 2). Non-Bayesian algorithms consist of least squares (LS) [8] and maximum likelihood algorithm (ML) [9]. In Bayesian algorithms, the current position is estimated by making full use of the prior information. Considering the uncertainty of the estimated position, the next position information is estimated by the previous position information, and the positioning accuracy is higher than that of non-Bayesian algorithm based. Kalman filter as a Bayesian algorithm based in linear Gaussian system can achieve the minimum variance estimation [9], but it cannot be suited to non-Gaussian nonlinear systems. Therefore, the position information for non-Gaussian and non-linear systems can be estimated by using Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). As anther one of the Bayesian algorithms, Particle Filter (PF) is a Monte Carlo method based on sequence importance sampling. The posterior probability distribution is estimated by a series of weighted particles, and the state of nodes is taken as a sample estimation and calculation, and can be well adapted to non-linear and non-Gaussian systems, but it suffers the problem of particle degradation [12].

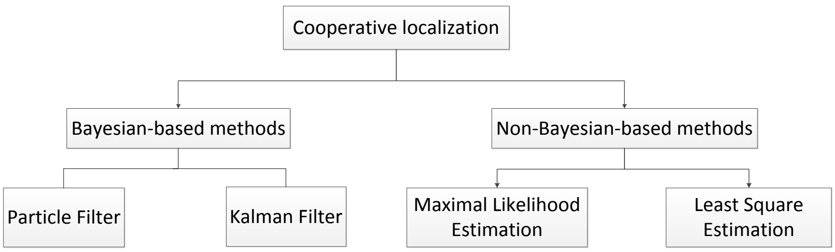

Fig.2 Collaborative location algorithm classification

In addition to above-mentioned classical estimation methods used for cooperative localization, some new Bayesian-based cooperative localization algorithms also came into being. In a foreign country, Ihler AT et al. in the Massachusetts Institute of Technology (MIT), the United States, proposed a cooperative localization algorithm based on nonparametric Belief Propagation (NBP) and PF to solve the problem of nodes self - localization in WSN [14]. In 2009, Win MZ and Wymeersch H et al. in MIT proposed a cooperative algorithm based on Factor Graph (FG) and Sum-Product Algorithm (SPA), ie SPAWN [15] (Sum-Product Algorithm over a Wireless Networks). SPA is used to calculate and transmit the message on FG, and finally the posterior probability distribution of position variable of each node is obtained.

2.2 Non-Bayesian Based Algorithm

Non-Bayesian algorithms include LS and ML which take the node position as the unknown parameter determined, and after acquiring measurement information from agent nodes and anchor nodes, the equation is established to solve the unknown parameter and obtain the position of nodes. The measurement information includes the Receive Signal Strength Indicator (RSSI), Time of Arrival (TOA), Time Difference of Arrival (TDOA) and Angel of Arrival (AOA) [4].

2.2.1 Least Square (LS)

Assuming that the coordinates of agent nodes and anchor nodes are described as $A=(x,y)$, $L=(x_{ki},y_{ki}), i=1\cdots m$, respectively. Agent nodes can receive the measurement information from anchor nodes, after receving more than 3 measurement information from anchor nodes, the equation will be established as $Ax = b$, where

$$A = -2\times\begin{bmatrix} (x_{k1}-x_{km}) & (y_{k2}-y_{km}) \\ \vdots & \vdots \\ (x_{k(m-1)}-x_{km}) & (y_{k(m-1)}-y_{km}) \end{bmatrix},\quad x=\begin{pmatrix} x \\ y \end{pmatrix}, \tag{1}$$

$$b=\begin{bmatrix} r_{k1}^2 - r_{km}^2 - x_{k1}^2 + x_{km}^2 - y_{k1}^2 + y_{km}^2 \\ \vdots \\ r_{k(m-1)}^2 - r_{km}^2 - x_{k(m-1)}^2 + x_{km}^2 - y_{k(m-1)}^2 + y_{km}^2 \end{bmatrix} \tag{2}$$

Due to the measurement error, the actual linear model should be $Ax + N = b$, where N is a k-1 dimensional random error vector. Using the LS principle, the value of x should minimize the model error $N = b - Ax$. The estimate of x with minimized $Q(x) = \|N\|^2 = \|b - Ax\|$. Let it be equal to 0, and the estimate of the unknown node can be solved,

$$\hat{x} = (A^T A)^{-1} A^T b \tag{3}$$

2.2.2 Maximum Likelihood Estimation (MLE)

MLE can be described as follows: Suppose there are m anchor nodes and u agent nodes, the coordinates of anchor nodes $(x_{k1}, y_{k1})\cdots(x_{km}, y_{km})$, the coordinate of agent node (x, y) and the distance between anchor nodes and unknown nodes $(d_{k1}\cdots d_{km})$. So we can obtain Eqs (4),

$$\begin{cases} (x_{k1}-x)^2 + (y_{k1}-y)^2 = d_{k1}^2 \\ \vdots \\ (x_{km}-x)^2 + (y_{km}-y)^2 = d_{km}^2 \end{cases} \tag{4}$$

Since this system is nonlinear , it is difficult to solve. The former $m-1$ and u -1 equations are subtracted from the last equation (referred to herein as the reference equation) into the following linear equation Eq. (5)

$$AX = B \tag{5}$$

where $A = -2\times\begin{bmatrix} (x_{k1}-x_{km}) & (y_{k2}-y_{km}) \\ \vdots & \vdots \\ (x_{k(m-1)}-x_{km}) & (y_{k(m-1)}-y_{km}) \end{bmatrix} x=\begin{pmatrix} x \\ y \end{pmatrix},\quad b=\begin{bmatrix} r_{k1}^2 - r_{km}^2 - x_{k1}^2 + x_{km}^2 - y_{k1}^2 + y_{km}^2 \\ \vdots \\ r_{k(m-1)}^2 - r_{km}^2 - x_{k(m-1)}^2 + x_{km}^2 - y_{k(m-1)}^2 + y_{km}^2 \end{bmatrix}$

Finally, the estimated value of the coordinate is acquired by LS, $\hat{x} = (A^T A)^{-1} A^T b$

2.3 Bayesian Based Algorithm

Since LS ignores the statistical properties of observed noise which results in a certain performance loss and ML ignores the prior information of estimated parameters. Therefore, the algorithm based on non-Bayesian method to some extent, is more inaccurate than that of based on Bayesian method. Bayesian methods make full use of prior information to estimate the current position considering the uncertainty of estimated position. Generally, Bayesian-based cooperative localization algorithm involves KF and PF.

2.3.1 Kalman Filter (KF)

Estimated position of KF is taken advantage of observations from previous and current moments, but each operation requires only the estimation of the previous time and the current observations without having to store the history data which reduces the storage requirements for the computer. And this algorithm is the optimal algorithm under the condition that the system is linear, the noise is Gaussian distribution and the posterior probability is also Gaussian.

First, we introduce a discrete control system. The system can be described by a linear stochastic differential equation

$$X(k) = AX(k-1) + BU(k) + w(k) \tag{6}$$

$$Z(k) = HX(k) + v(k) \tag{7}$$

where $X(k)$ which is the amount of control of the system at all times is the system state at time k . A and B are system parameters, and for multi-model systems, they are matrices. $Z(k)$ is the measurement value at time k . H is the parameter of the measurement system, and for the multi-measurement system, H is the matrix. $w(k)$ and $v(k)$ represent the process and the measurement noise, respectively. And assuming that they are subject to be Gaussian white noise and their covariance are Q and R respectively. For systems whose processes and measurements are both Gaussian white noise that meet the linear stochastic differential system, KF is the optimal information processor. The covariance is used to estimate the optimal output of the system.

First we use the system's process model to predict the next state of the system. Assuming that the current system state can be predicted through previous estimated state based on the system model,

$$X(k|k-1) = AX(k-1|k-1) + BU(k) \tag{8}$$

where $X(k|k-1)$ denotes the predicted result by using the previous state. $X(k-1|k-1)$ indicates the optimal result of the previous state. and $U(k)$ is the control of the current state. If there is no control, it can be zero. So far, the system results have been updated, but the corresponding covariance for $X(k|k-1)$ has not been updated yet.

$$P(k|k-1) = AP(k-1|k-1)A^T + Q \tag{9}$$

where $P(k|k-1)$ denotes the covariance corresponding to $X(k|k-1)$. $P(k-1|k-1)$ indicates the covariance of $X(k-1|k-1)$. A^T denotes the transpose matrix of A . Q is covariance, the, and Q is the covariance of system process.

Now we have the estimated current state and then collect the measurement of current state. After combining the estimated and measured values, optimal estimation $X(k|k)$ can be obtained.

$$X(k|k) = X(k|k\text{-}1) + Kg(k)(Z(k) - HX(k|k-1)) \tag{10}$$

where Kg is the Kalman gain.

$$Kg(k) = P(k|k-1)H^T/(H * P(k|k-1)H^T + R) \tag{11}$$

So far, the optimal estimation $X(k|k)$ of the k state has been obtained. However, in order to keep the KF running until the end of the system process, covariance of $X(k|k)$ of the k state should be updated.

$$P(k|k) = (I - Kg(k)H)P(k|k-1) \tag{12}$$

where I denotes unit matrix, for a single model, I = 1. When the system enters $k+1$ state, $P(k|k)$ indicates the covariance of last time like $P(k|k\text{-}1)$ of Eq. (12). In this way, the algorithm can be autoregressive. And Eqs. (8) to (12) are the five basic principles of KF.

2.3.2 Particle Filter (PF)

PF is a Monte Carlo method based on sequence importance sampling. The system model can be described as,

$$x^{(t)} = f(x^{(t\text{-}1)}, u^{(t-1)}) \tag{13}$$

$$z^{(t)} = h(x^{(t)}, v^{(t)}) \tag{14}$$

where $f()$ represents the state transition function. $x^{(t-1)}$ indicates the last state. $u^{(t-1)}$ indicates the Gaussian state transition noise whose mean value is zero and variance is Q. $h()$ indicates the measurement function. $v^{(t)}$ indicates the measurement noise whose mean value is zero and variance is R.

The core idea of PF is to estimate the posterior probability through priori probability,

$$P(x^{(t)} \big| z^{(1:t)}) = \frac{1}{\eta} P(z^{(t)} \big| x^{(t)}) P(x^{(t)} \big| z^{(1:t-1)}) \tag{15}$$

where $\eta = P(z^{(t)} \big| z^{(1:t-1)}) = \int P(z^{(t)} \big| x^{(t)}) \cdot P(x^{(t)} \big| z^{(1:t-1)})$ (16)

The prior information in Eq. (15) can be expressed as,

$$P(x^{(t)} \big| z^{(1:t-1)}) = \int P(x^{(t)} \big| x^{(t-1)}) P(x^{(t-1)} \big| z^{(1:t-1)}) dx^{(t-1)} \tag{17}$$

where $z^{(1:t-1)}$ and $z^{(1:t)}$ denote the measurement information from 1 to t-1 and 1 to t, respectively.

However, the posterior probability distribution is difficult to obtain when it comes to real situation, and the sample value is usually obtained using a known and easy-to-sample importance probability density $\pi(x^{(t)} \big| z^{(1:t)})$. When the sample is large enough, $\pi(x^{(t)} \big| z^{(1:t)})$ can be approximately equal to $P(x^{(t)} \big| z^{(1:t)})$. Then position is then estimated by normalizing weights and resampling,

$$P(x^{(t)} \big| z^{(1:t)}) \approx \sum_{i=1}^{N} \{\omega^{(t)}\}_i \delta(x^{(t)} - \{x^{(t)}\}_i) \tag{18}$$

where $\{\omega^{(t)}\}_i$ indicates the weight of i th particle at time t. $\{x^{(t)}\}_i$ denotes the position of i th particle at time t. N represents the total number of particles. $\delta()$ represents the Dirac function.

After obtaining the posterior probability distribution, we can estimate the position of the node,

$$E(x^{(t)} \big| z^{(1:t)}) = \int P(x^{(t)} \big| z^{(1:t)}) \cdot x^{(t)} dx^{(t)} \approx \sum_{i=1}^{M} \{\omega^{(t)}\}_i \cdot \{x^{(t)}\}_i \tag{19}$$

In order to avoid particle degradation, resampling is essential in PF. The importance of resampling is currently the most common resampling method, which relies on the retention of larger particles and the elimination of smaller particles.Therefore, the algorithm flow chart of PF can be expressed as Fig.3.

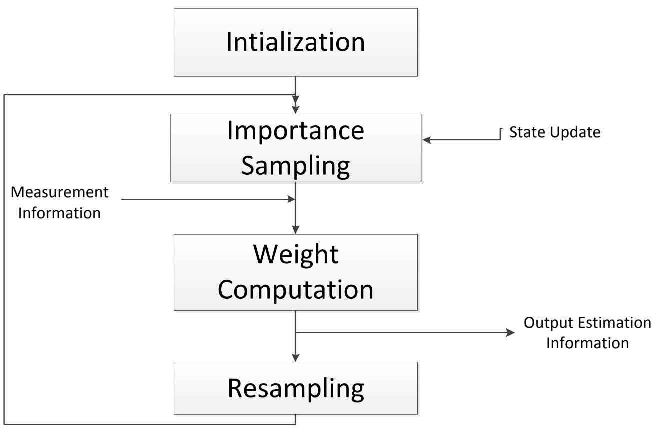

Fig.3 The flow chart of PF

3. PF Based Cooperative Localization

PF is considered to be a satisfactary choice for cooperative localization because non-Bayesian based cooperative localization takes no account of uncertainty of estimated position, KF is not suitable for non-linear system and the computational cost is large for EKF though it can adjust to non-linear system. Due to suffering from degeneracy of particles, many scholars have done a corresponding study on this issue recent years.

Shan et al. proposed a cooperative localization algorithm for nonparametric estimation based on PF using Gibbs sampling method to obtain high quality particles to solve the degeneracy problem [16]. Li et al. improved likelihood function of PF by establishing the Gaussian dynamic model, and proposed that the non-parametric estimation of the adaptive PF under the condition of uncertainty measurement [17]. Li et al. proposed PF based on particle swarm optimization. In the process of generating the sampled particles, the particle swarm optimization algorithm is combined to make the smaller particles not be removed during resampling to keep the diversity of particles [18]. Tseng P.H et al. proposed cooperative self-localization under line-of-sight and non-line-of-sight conditions, and used the multi-model importance sampling to filter the location of mobile nodes and the channel conditions [19]. Martino et al. proposed an interactive parallel PF cooperative localization algorithm in which the sampling patterns of each particle are different and cooperate with each other to obtain a global optimal estimate of the hidden Markov chain [20]. Teng et al. used KL divergence to calculate the distance between each particle to reduce the cost of resampling [21]. Wu et al. divided the SLAM algorithm into two parts, one of which is the positioning of the robot, the other is the positioning of the sensor nodes. And then the inaccuracy problem in SLAM was solved by using improved marginal PF cooperative localization [22].

4. Conclusion

The cooperative localization in WSN involves Bayesian based method and non-Bayesian based method. In this paper, the related algorithm proposed in recent years is summarized. By introducing the principle of each algorithm, the reader can understand deeply. We introduce related research of PF recent years in detail in Section 3 due to its outstanding performance in non-linear and non-Gaussian system.

It can be seen from the related research that most scholars focus on the problem of particle degradation in particle filter, the selection of sampling particle model and the resampling method in indoor positioning. For further research, it can be divided into two parts: the first part is to improve likelihood function; the other part is to utilize PF cooperative localization into outdoor environment such ocean monitoring and tracking of nodes at sea.

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