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Research article

A novel cooperative localization algorithm using enhanced particle filter technique in maritime search and rescue wireless sensor network

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ABSTRACT

Maritime search and rescue (MSR) play a significant role in Safety of Life at Sea (SOLAS). However, it suffers from scenarios that the measurement information is inaccurate due to wave shadow effect when utilizing wireless Sensor Network (WSN) technology in MSR. In this paper, we develop a Novel Co-operative Localization Algorithm (NCLA) in MSR by using an enhanced particle filter method to reduce measurement errors on observation model caused by wave shadow effect. First, we take into account the mobility of nodes at sea to develop a motion model—Lagrangian model. Furthermore, we introduce both state model and observation model to constitute a system model for particle filter (PF). To address the impact of the wave shadow effect on the observation model, we develop an optimal parameter derived by Kullback-Leibler divergence (KLD) to mitigate the error. After the optimal parameter is acquired, an improved likelihood function is presented. Finally, the estimated position is acquired

1. Introduction

As the last defense line for life safety at sea, maritime search and rescue (MSR), represents the most important step in the maritime traffic accident. Hence, it attracts significant attentions from many researchers and industrial practitioners. Traditional MSR relies on the rescue party, where the person in distress has to wait passively for being rescued launched by Rescue Coordinate Center (RCC). However, to implement MSR with Wireless Sensor Network (WSN), people who carry sensors physically at hands can indicate the position automatically. As a result, the efficiency of search and rescue can be raised by one order of magnitude. WSN, which has been increasingly applied to controlling, monitoring and tracking problems recently [1,2], is a self-organizing network comprised of numerous sensor nodes with low cost and low power [3]. Central to the WSN design, localization denotes one of the major bottlenecks when we deploy a large-scale WSN to the monitoring area. In recent years, various methods have been developed to improve the localization accuracy under different applications [4].

As for the localization in WSN, there are two kinds of nodes that should be noticed: unknown nodes and anchor nodes. Anchor nodes with GPS can be aware of their position while unknown nodes cannot. Basically, node localization mainly involves co-operative localization scheme and non-cooperative localization scheme. In non-cooperative localization scheme, unknown nodes receive signals only from anchor nodes. For non-cooperative localization algorithms at sea, authors in [5–7] have presented. In [5], a real time localization method with combining improved centroid algorithm and the microelectronic system was proposed. The authors in [6] presented an improved Monte Carlo algorithm to position mobile nodes. In [7], a 3D localization method was introduced by deploying three anchor nodes on the rescue helicopter. However, those localization algorithms at sea are non-cooperative. Deviation errors from the wave shadow effect could increase over time.

Generally, cooperative localization scheme outperforms non-cooperative localization scheme [8]. In cooperative localization scheme, nodes receive signals which are transmitted from anchors and adjacent nodes [9]. Fig. 1 illustrates the diagram of cooperative localization at sea in WSN. Individuals who carry lifejackets with unknown nodes can communicate with ships and crafts disposed of GPS. And they can communicate with anchor nodes and other unknown nodes deployed at sea without fixed position as well.

Cooperative localization mainly involves both non-Bayesian based and Bayesian based algorithms. Non-Bayesian based algorithms, which include least squares (LS) [10] and maximum likelihood (ML) [11], do not take into account the uncertainty of the estimated position and thus degrade the localization accuracy. On

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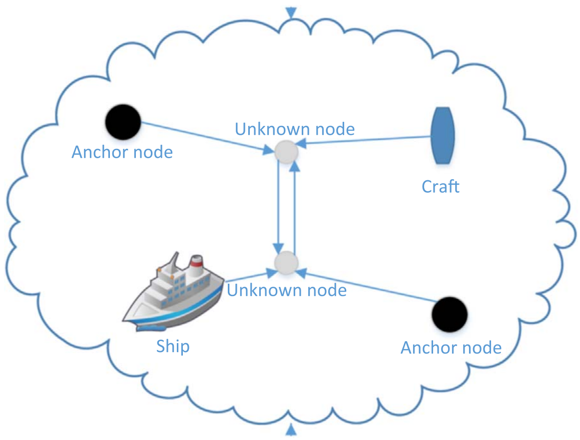

Fig. 1. Diagrammatic sketch of Cooperative localization in MSR WSN.

the contrary, Bayesian based algorithms, which make full use of the prior information of nodes to estimate position, are expected to be a better estimation method. Kalman Filter (KF) as a kind of Bayesian based algorithm can achieve minimum variance estimation by obtaining the model of noise [12]. However, it is difficult to know the precise noise model in practice. Therefore, as an estimation method that does not need to know the precise model of noise, H_∞ filter, which considers the noise as random finite signals, has been developed in engineering applications like fault identification and estimation [13]. And H_∞ filter can achieve minimax estimation. In [14], a mixed H_-/H_∞ fault detector method for the steering actuator of the electric ground vehicle (EGV) was proposed. A finite-frequency H_∞ observer was designed to estimate the sideslip angle of EGV [15]. And H_∞ filter was utilized in Markovian jump systems (MJSs) as well [16–18]. To mention a few, the authors investigated H_∞ filter design for continuous-time MJSs with deficient mode information in [16]. A H_∞ filter for two-dimensional MJSs with state-delays and deficient mode information was designed in [17].

It should be noticed that both KF and H_∞ filter are not suitable for non-linear and non-Gaussian systems. In non-linear systems, there are uncertainties caused by modeling errors and external disturbances. In order to reduce these uncertainties in non-linear systems, many effective schemes were proposed such as adaptive fuzzy control [19] and adaptive sliding mode control [20,21]. To mention a few, an adaptive fuzzy control was presented to solve the uncertainties caused by unmodeled dynamics and fuzzy dead zone in [19]. The authors proposed an optimal guaranteed cost sliding mode control for type-2 fuzzy time–delay systems with uncertain parameters hidden in membership functions in [21]. As a non-linear estimator, Particle Filter (PF) is used to solve the errors in non-linear systems as well. PF being a sequence Monte Carlo method can adapt to non-linear and non-Gaussian systems. In PF, the posterior probability distribution is estimated by a series of weighted particles, and nodes positions are estimated after the acquirement of the posterior probability distribution.

Traditional PF has the problem of particles degeneracy. The solution basically contains the improvement of the quality of particles [22–24] and resampling [25–27]. To mention a few, Shan *et al.* utilized Gibbs sampling method to obtain high-quality particles [22]. The authors in [26] introduced a new resampling method called Kullback-Leibler divergence (KLD) resampling. It can select resampling particle adaptively. For other modified PF algorithms, an adaptive particle filter method under uncertainty measurement by improving the likelihood function was proposed [28]. The authors proposed a cooperative localization based on PF using the multi-model importance of sampling [29]. However, the aforementioned cooperative PF algorithms only work well for the indoor environment, while their performance is not acceptable due to the wave shadow effect at sea.

According to the issues mentioned above, we develop a novel cooperative localization algorithm (NCLA) based on an enhanced PF in this paper. By deploying sensor nodes in search and rescue area, Zigbee protocol is used to form a self-organizing WSN in the area. After that, Lagrangian trajectory motion model is established by considering the impact of wind and wave on nodes motion. After the system model is established, to reduce the error caused by the wave shadow effect, an optimal parameter is introduced and derived by using KLD. In addition, an improved likelihood function is presented by the optimal parameter. Finally, the position of nodes are acquired by using improved likelihood function with residual-systematic resampling (RSR).

The remainder of the paper is organized as follows. In Section 2, we formulate the problem of cooperative localization. In Section 3, we introduce the system model. In Section 4, we present our proposed algorithm. In Section 5, we evaluate the proposed algorithm with simulation experiments. In the last section, Section 6, we conclude this paper.

2. Problem formulation

WSN is established by Zigbee protocol after sensor nodes are deployed in search and rescue area. Assuming that there are s anchor nodes and n unknown nodes in the network. Let S and N represent the set of anchor nodes and unknown nodes, respectively. So, we can describe that $n \in N$, $s \in S$. The position of anchor nodes at time t can be expressed as $A = [a_1^{(t)} a_2^{(t)} \cdots a_s^{(t)}]^T$, T represents transpose operation. And the position of unknown nodes at time t can be expressed as $x^{(t)} = [x_1^{(t)} x_2^{(t)} \cdots x_n^{(t)}]^T$. The position of anchor nodes and unknown nodes are affected by wind and wave because they are not fixed at sea.

In cooperative localization, unknown nodes can not only receive measurement information from anchor nodes within communication range but also from adjacent unknown nodes. There are several measurement models for WSN such as angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA) and received signal strength indicator (RSSI). Considering the low need of hardware, communication costs and the need for extensive deployment of nodes at sea, we utilize RSSI as the measurement model. RSSI mainly uses Radio Frequency (RF) signal. Since the error is generated from multipath propagation, NLOS (non-line of sight) and other factors, RSSI ranging model can be expressed by the propagation path-loss model.

$$RSSI_n^{(t)} = power - PL(d_0) - 10k \lg(\frac{d}{d_0}) \tag{1}$$

where $RSSI_n^{(t)}$ indicates an unknown node n received signal strength value at time t. $power$ denotes the transmitting power of nodes. $PL(d_0)$ is the signal strength loss value when the reference distance is 1 m. k is the path loss index which depends on the surrounding environment. d denotes the distance between two nodes.

Basically, after the transmitting power value and received power value are recognized, the distance between two nodes can be known. So Eq. (1) can be transformed into Eq. (2).

$$d = 10^{\frac{power - PL(d_0) - RSSI_n^{(t)}}{10k}} \times d_0 \tag{2}$$

Assuming that $\forall\, n \in N$ receives RSSI from anchor nodes $s \in S$ at time t, the distance between them can be expressed as,

$$\rho_{ns}^{(t)} = \|x_n^{(t)} - a_s^{(t)}\| + \xi^{(t)} \tag{3}$$

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