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Noise-aware fingerprint localization algorithm for wireless sensor network based on adaptive fingerprint Kalman filter

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ABSTRACT

The indoor localization technique is one of the key technologies in the field of wireless sensor network (WSN) research. Fingerprint localization that uses the received signal strength indication (RSSI) is a type of indoor positioning technology that can be applied to a noisy WSN environment. This work proposes a noise-aware fingerprint localization algorithm for WSNs based on an innovative adaptive fingerprint Kalman filter (AFKF), which is effective at refining the computational results of the state-of-the-art fingerprint positioning algorithm in noisy environments. This novel AFKF is composed of a Kalman filter (KF), a noise covariance estimator (NCE) and a fingerprint Kalman filter (FKF). First, the KF filters the RSSI with the measurement noise, and then, the NCE is aware of the noise covariance of the filtered RSSI. Finally, the FKF refines the node position that is estimated by the existing fingerprint localization algorithm according to the filtered RSSI and the perceived noise covariance. Our proposed algorithm not only overcomes the limitation of the current range-based localization algorithm but also solves the problem of the present fingerprint localization algorithm; in other words, it can be applied in a situation in which an accurate RSSI-distance model cannot be established and is applicable to a scenario that has unknown or time-varying noise. The results of practical experiments and numerical simulations show that regardless of how the target nodes are placed or how many beacon nodes there are as well as whether the measurement noise is strong or weak or whether the calibration cell is large or small, the proposed algorithm improves the accuracy of the widely applied fingerprint positioning algorithms by at least 50%. These algorithms include the nearest neighbor algorithm (NN), the K-nearest neighbor algorithm (KNN), the weighted K-nearest neighbor algorithm (WKNN), and their refinement algorithms, namely, the position Kalman filter (PKF) and the FKF.

1. Introduction

Since the global positioning system cannot provide localization services in a room, the indoor positioning technique has become a hot spot of research. At present, fingerprint localization based on radio-frequency signals of wireless networks is one of the widely applied indoor positioning technologies [1–3]. Therefore, the fingerprint positioning algorithm using the received signal strength indication (RSSI) in wireless sensor networks (WSNs) is proposed [4–6]. The WSN is a type of ad-hoc network that is composed of many nodes that are equipped with sensors, transceivers, and microcontrollers [7,8]. In most WSNs, the strength of the radio-frequency signal, namely the RSSI, is easy to extract from the transceiver. These measured RSSIs and the corresponding measurement positions constitute a radio map that is used to estimate the location of the node in the fingerprint localization.

According to whether a measurement of the distance between the nodes in the process of localization is required or not, the positioning algorithm for the WSN can be divided into two categories: one category is range-based, and the other is range-free [9–12]. In addition to the fingerprint localization algorithm, there are other range-based algorithms that can be applied to indoor positioning. These algorithms mainly include the time of arrival (TOA), the time difference of arrival (TDOA), and the angle of arrival (AOA) [13–15]. Although they can be employed to calculate the position of the node in the WSN, a highly precise time synchronization of the network is required. In general, it is difficult to achieve this requirement for the WSN with a limited energy and communication bandwidth. Because the RSSI-based fingerprint positioning does not require strict network synchronization, it is especially suitable for the resource-constrained WSN.

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Currently, fingerprint localization is composed of main two stages: one stage is the off-line calibration stage, and the other is the online positioning stage. During the off-line calibration, the corresponding relationship between the mean value of the measured RSSI, namely, the calibrated fingerprint, and the measurement location, namely, the calibration point, is set up. During the online positioning, the fingerprint in the radio map and the RSSI measured by the target node located at an unknown position are matched to search one or more adjacent calibration points. Finally, these calibration points and their weights are utilized to compute the location of the target node. Currently, the most widely adopted fingerprint matching algorithms have the nearest neighbor algorithm (NN), the K-nearest neighbor algorithm (KNN), and the weighted K-nearest neighbor algorithm (WKNN) [16–18], which are often used as the performance benchmark of the newly proposed fingerprint positioning algorithm. The NN uses only one nearest calibration point as the location estimate of the target node, while the KNN directly uses the average coordinates of the multiple nearest calibration points as the estimated node position. Obviously, the location estimate of the KNN is more accurate than that of the NN. In contrast to the KNN, the WKNN assigns different weights to the different nearest calibration points. As a result, the node position estimated by the WKNN is typically more accurate than that estimated by the KNN.

However, the above-mentioned algorithms have no immunity to the measurement noise of the RSSI. Because there is no established RSSI-distance model that can be used as the measurement model of the position observation system, the traditional Kalman filter (KF) cannot be directly utilized to filter the RSSI's measurement noise in the fingerprint localization algorithm via the method of the RSSI measurement estimating the node position [19,20]. Two new KFs for removal of the noise of the RSSI measured during fingerprint localization are created, namely, the position KF (PKF) [21,22] and the fingerprint KF (FKF) [23,24]. The PKF uses the position estimated by the fingerprint positioning algorithm as the system measurement instead of the RSSI, which does not directly filter the noise of the RSSI, but only indirectly reduces the fluctuations in the position estimation caused by the RSSI's noise. Consequently, it is extremely limited to the noise-filtering effect of the RSSI. Unlike the PKF, the FKF directly uses the measured RSSI as its system measurement, in such a way that it has a better filtering effect on the RSSI's noise. Nevertheless, when the RSSI has a large or time-variant noise, the FKF's filtering effect will become rather poor.

In this paper, we propose a noise-aware fingerprint localization algorithm for the WSN, which is implemented based on an innovative adaptive fingerprint Kalman filter (AFKF). The novel AFKF is composed of a KF, a noise covariance estimator (NCE) and a FKF. In the AFKF, the KF is responsible for reducing the noise of the measured RSSI, the NCE is responsible for sensing the noise covariance of the filtered RSSI, and the FKF uses the filtered RSSI and the perceived noise covariance to refine the results of the fingerprint matching algorithm.

1.1. Contributions

Our main contributions are listed as follows:

- An innovative adaptive fingerprint Kalman filter is constructed, which makes the fingerprint Kalman filter possess the ability to adapt to changes in the RSSI noise. As far as we know, the novel adaptive fingerprint Kalman filter is currently the only class of Kalman filters that can be used to filter the RSSI's measurement noise in the process of fingerprint localization in the case of unknown noise or time-varying noise.
- A noise-aware fingerprint localization algorithm for the wireless sensor network based on the novel adaptive fingerprint Kalman filter is designed, which can greatly improve the accuracy of the state-of-the-art fingerprint positioning algorithm. To the best of our knowledge, it is the only type of fingerprint localization algorithm that has a noise-adaptive ability.
- The effectiveness and efficiency of our proposed algorithm are verified by a large number of practical experiments and numerical simulations under different network parameter settings. Extensive results of experiments and simulations show that regardless of how the target node is placed or the number of beacon nodes or whether the measurement noise is strong or weak or whether the calibration cell is large or small, the proposed algorithm increases the accuracy of the existing fingerprint localization algorithm by at least 50%.

1.2. Organization

The organizational structure of this paper is the following. Section 2 introduces the work related to the fingerprint positioning algorithm. Section 3 describes the problem formalization of fingerprint localization. Section 4 summarizes the existing fingerprint Kalman filtering algorithm, while Section 5 presents the proposed noise-aware fingerprint localization algorithm. Section 6 shows the results and analysis of the experiments and simulations. Finally, Section 7 concludes the paper.

2. Related work

At present, the algorithms used for indoor fingerprint localization mainly contain the neural network algorithm, the machine learning algorithm, the pattern matching algorithm and so on [25–27]. The neural network algorithm is to determine the mapping path between the input and output through training on the existing data. The measured RSSI will be mapped to the most possible node location based on the established neural network graph. Due to the presence of the measurement noise, the fingerprint positioning algorithm using the neural network is likely to map the noisy RSSI to the wrong path, in other words, to produce an inaccurate node position estimation. Thus, it can be seen that this algorithm is not suitable for fingerprint localization in a noisy environment. The machine learning algorithm is to mine useful information from a large amount of data in such a way that a previously unknown connection between entities can be established. According to the information obtained via mining, the measured RSSI will be assigned to the corresponding fingerprint classification. The coordinates of the calibration point in this fingerprint classification are seen as the estimated node position. Similar to the neural network algorithm, a noisy RSSI could cause the fixed classification relationship established by the machine learning algorithm (based on historical data) to be invalid. In contrast, the pattern matching algorithm, whose outstanding representative is the WKNN, is always efficient at selecting the calibration points that are closest to the target node.

Although the WKNN algorithm can be used for fingerprint positioning using noisy RSSIs, its node location estimate is not optimal in a noisy environment. Currently, some algorithms have been proposed to improve the localization accuracy of the WKNN. These algorithms can be divided into two classes: one class is to change the number of selected nearest neighbor calibration points in the WKNN [28–30], and the other is to redefine the weight calculation of the calibration point [31–33]. Since the number of nearest neighbors plays little role in the estimation results of the node position, the improvement effect of the former algorithm on the positioning precision of the WKNN is rather limited. Although the latter algorithm attempts to increase the localization accuracy of