Comparing Centralized Kalman Filter Schemes for Indoor Positioning in Wireless Sensor Network

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***Abstract*—Kalman filter (KF) have been widely used in tracking systems to reduce measurement noise. However, KF are not perfect when suffering severe noise and fluctuating wireless condition in indoor environments. We propose a novel computing architecture for wireless sensor networks (WSN) to overcome these drawbacks, which divides the positioning system into three components: measurement, pre-processing and data-processing. We developed a voting filter and an averaging filter in pre-processing to reduce measurement noise for later processing. During data-processing, a Kalman filter is used to track the positions. We also implement another scheme, low pass filter with KF, to estimate the positions with the knowledge of geographic information. Three realistic experiments are set up using the sensor equipment nanoPAN 5375 to evaluate these methods. Comparing the experimental results, low pass filter with KF is most suitable to be used in indoor positioning.**

***Index Terms*—indoor positioning, Kalman filter, wireless sensor network**

I. Introduction

Location detection and positioning systems for wireless sensor network (WSN) have become very popular in recent years. These systems have been used successfully in many applications, such as location detection of products stored in a warehouse, medical personnel or equipment in a hospital as in [1].

Different techniques are used to track the positions for indoor systems [2]–[4]. For instance, the angle of arrival (TOA), received signal strength (RSS) in RADAR system [3], [4], time-of-arrival (TOA) and its improved metrics: time-difference-of-arrival (TDOA) [2] and time-of-flight (TOF) [2]. TOF measures the round-trip time of packet and average the the result the results together to reduce the impact of time-varying errors [2]. It is a promising solution for its low cost and feasible for the capacity of real-time application.

However, it is not easy to model the radio propagation for WSN in indoor environments, especially the time of delay. The low signal-to-noise ratio (SNR), severe multi-path effects, reflection and link failure cause extreme measurement errors and data loss [1]. Several publications introduce Kalman filter (KF) into WSN systems [5]–[8]. Kalman filter, a recursive linear filtering model, is widely used in positioning systems to estimate tracks through noisy measurements [3], [9], [10].

Although KF offers several advantages, it can still produce errors if the measurement noise is too high. Some propose distributed KF to reduce the noise in a distributed way [6], [7], but these sensors have global information, whereas sensors can only provide partial range values in the real-world positioning system. Moreover, RADAR implements Kalman filter, according to [3], but the environment changes are not considered strongly which makes it not suitable for real world application.

To overcome these problems and implement a real-time tracking system, we propose a novel centralized architecture with three components: measurement, pre-processing and data-processing. Two schemes in the pre-processing component are introduced: voting filter (VF), and averaging filter (AF). These filters reduce noise in measurement data, but there is still noise left. According to our experimental results, the noise lead to positions outside of the sensor range. Thus, for data-processing, we combine low pass filter (LPF) with KF (LPF-KF) to improve positioning. To evaluate our three schemes, we set up experiments and compare the performance with each scheme. Experimental results show that integrated schemes shows different performance in different scenarios and conclude that LPF-KF is a better scheme for indoor positioning.

II. System Architecture

Our architecture consists of three components: measurement, pre-processing and data-processing, as shown in Fig. 1. Measurement is designed as the physical interaction between anchors and a fusion center to generate measurement data. The fusion center can be implemented in the mobile node. In our system, it is located in a remote server. Pre-processing and data-processing are implemented in the fusion center. Pre-processing attempts to deal with link failure, invalid data or data loss and lowering the noise to improve positioning computed during later stages. Data-processing estimates the positions based on Kalman filter algorithm to provide final positions.

The physical devices in our WSN positioning system consist of the mobile node as the target, the anchors and the fusion center. The mobile node and the anchors send round-trip packets to each other. The measurement component measures the range from the anchors according to the time stamp of these packets based on time-of-flight (TOF). Then, the mobile node sends the measured ranging values to the fusion center.

Because of high noise in measurement, a pre-processing component attempts to reduce noise of range values and adapt to link failures to provide previously processed data for the later component. For indoor positioning, we assume that the target moves with a constant low speed. The sensor node can

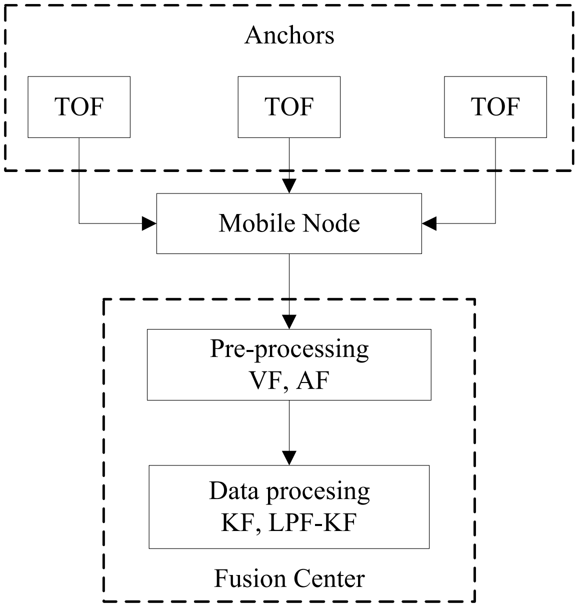


Fig. 1. System Architecture

sample bursts of rangings at a very high rate and send them to the fusion center. During such a sampling period, we assume that the node does not move, because the movement will not be distinguishable from noise. The burst is a unit for processing by the voting filter (VF) or the averaging filter (AF).

In data processing, it calculates the positions by lateration and corrects the result with KF. However, there are still measurement errors left. Thus, we develop a filter, which integrates low pass filter and Kalman filter (LPF-KF), to filter out rangings outside of the area.

III. Kalman Filter Modeling in WSN

Kalman filter is a set of equations that provides a method to estimate the position of a process. This series of equations consist of two steps: prediction (estimation equations) and correction (measurement equations), according to [9] and [10].

A. Estimation Equations

In the prediction step (estimation equations), the estimated value can be expressed as:

$$x_{k+1} = Ax_k + q_{k+1}, \tag{1}$$

Here, the state vectors $x_k = [X_k, \hat{X}_k, Y_k, \hat{Y}_k]^T$ are the positions X_k and Y_k and velocities $\hat{X}_k$ and $\hat{Y}_k$ at sample k. The state transition matrix A in equation (1) is time invariant and is given by

$$A = \begin{pmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{pmatrix}, \tag{2}$$

Matrix A is the transition matrix which predict the next state from the previous state based on a constant movement model, and the element Δt is the sample period of each step. And $q_k = [x_{error}, \dot{x}_{error}, y_{error}, \dot{y}_{error}]$ is problistic vector of processing errors and the noise due to the uncertainty in estimation. The elements x_{error} and y_{error} are transition position errors, and $\dot{x}_{error}$ and $\dot{y}_{error}$ are the velocity errors.

B. Measurement Equations

The correction step (measurement equations) can be expressed as:

$$z_k = Hx_k + r_k, \tag{3}$$

The matrix H is a projection to turn x_k into a position, as shown in equation (4)

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \tag{4}$$

The $r_k = [x_{error1}, y_{error1}]^T$ is the measurement noise vector. And the final filtered result $\hat{x}_k$ can be expressed as:

$$\hat{x}_k = x_k + K_k(z_k - Hx_k). \tag{5}$$

The 2×4 matrix K_k in equation (5) is chosen to be the Kalman gain that minimizes the measurement covariance, see [10].

IV. Integrated Schemes for Positioning System

We detail the proposed schemes to assist our Kalman filter to process the measurement data in order to get more precise positions. The first two schemes, AF and VF are developed for pre-processing. The third scheme combines LPF with KF in the data-processing.

A. Voting Filter with Kalman Filter (VF-KF)

The voting filter with Kalman filter (VF-KF) reduces the measurement noise and link failures by voting the representative ranging values of sampling periods. During pre-processing, the measurement is collected into groups of a sampling period. The majority of values in this group are selected by the majority of range values according to the voting theory in [11]. In our scheme, 15 samples are grouped for each sampling period. Then, the chosen values are sent to the data processing component. During voting, link failures and invalid values such as extremely large rangings are discarded if they do not get a majority votes. In this way, small errors are reduced and robustness is strengthened. But this filter does not reduce the measurement noise, so KF in data-processing will do for this part.

B. Averaging Filter in Kalman Filter (AF-KF)

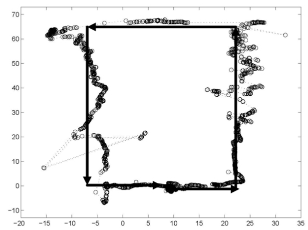
To provide a fast algorithm for real-time application, the averaging filter is proposed for the pre-processing component. AF assumes that range values fluctuate in a small range during a sampling period. The average value represents the range state, and reduces the noise to some extend. The procedure of AF is similar to VF. AF collects every 15 measurements into a group and gives the average values, then sends them to the data processing component. This is much simpler and faster. Although AF discards link failure information and some extreme values, interference, which causes longer packet delays and leads to larger ranging values, can still not be reduced. This is left to the data-processing.

C. Low Pass Filter in Kalman Filter (LPF-KF)

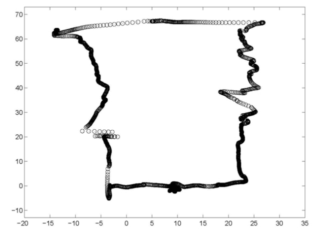
LPF-KF is to correct the measurement value using the information of indoor region. LPF-KF has the information boundaries of the layout, such as the size of a room. It filters out the positions out of the boundaries. This scheme integrated low pass filter with Kalman filter. If the data are within the bound of region, the filter works like a Kalman filter, which calculated the positions according the prediction and correction equations. But if the data is out of bounds, the filter just believes the predicted value obtained from previous state.

V. Experimental Evaluation

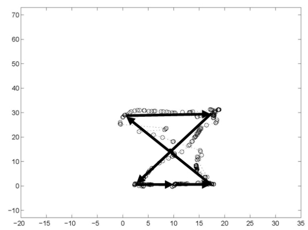
To evaluate our methods, we set up a serial experiments both in outdoor yard and indoor environment such as our lab. The first experiment is to analyze the performance of Kalman filter in the outside yard with lower noise and less reflection. The yard is 80 meters long and 60 meters wide. Here, the wireless environment is constant and distribution of noise is almost Gaussian. The four anchors are set at the position of $(0, 0)$, $(19.5, 0)$, $(19.5, 32.8)$ and $(0, 32.8)$. The filtering results are shown in Fig. 2.



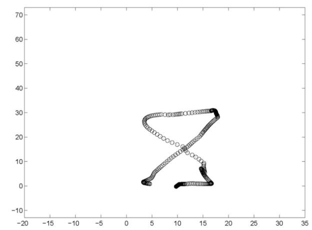
(a) Scenario I: Measurement Positions



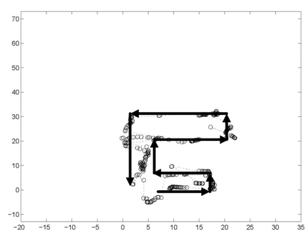
(b) Scenario I: Filtered Positions



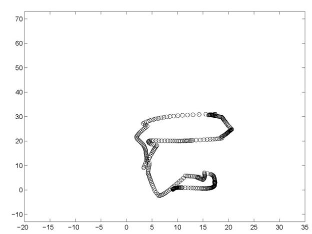
(c) Scenario II: Measurement Positions



(d) Scenario II: Filtered Positions



(e) Scenario III: Measurement Positions



(f) Scenario III: Filtered Positions

Fig. 2. Experiment Results: Comparison between the measurement positions and filtered positions

In Fig. 2, the left column depicts the original measurement positions filtered by AF. The arrow solid line represents the true tracking path during the experiment. The circle dash line is the measured positions. The right column points out the positions that are filtered by KF for each scenario. The tracking paths are quite similar to the true path after filtering. This experiment demonstrates Kalman filter can reduce noise effectively and can be used in real-time application.

Two indoor experiments are constructed in a building. The sensors are from the commercial equipments, with nanoPAN 5375 RF module at 2.4GHz [12], LPC 2387 as microcontroller [13] and CC1101 as radio transceiver [14]. Three anchors and one node as target are involved in experiments. The experiments are performed during daytime with high noise and interference. The first experiment is in a corridor with field of 1.85 meters wide and 6.33 meters long. Anchors are located at (0,0), (0,6.33) and (-3.55,0), which are in the corner of the corridor. The boundaries are from -5 to 0 in x-axis and 0 to 7 in y-axis. The target node is carried by a person moves through the corridor and turn right and forward 6 to 7 meters. Fig. 3 is the processing results in this scenario.

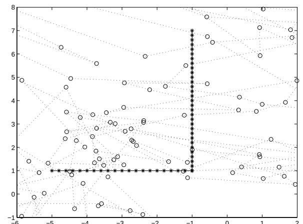
Fig. 3(a) represents the true tracking path in star-solid line and measured results in circle-dash line. As shown in Fig. 3(b) and 3(c), VF-KF and AF-KF have almost the same performance, and some values are outside of the boundaries. LPF-KF tends to be more similar to the true path than the other two.

Fig. 4 represents the results of a second experiment which is constructed in our lab-office with the width of 2.65 meters and length of 5.60 meters. The noise and reflection are more severe than the corridor, thanks to the wireless interference, obstacles and complete close environment. Three anchors are located at (0,0), (2.65,0) and (2.65.5.60), which are the corners of the lab. The expected path is a straight star-solid line move through the lab with a constant speed, as shown in 4(a).

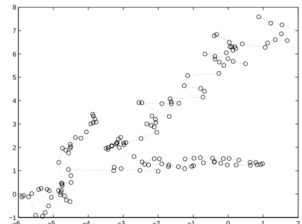
As shown in Fig. 4, due to severe interference and noise, the three filters do not produce the expected path. AF-KF and VF-KF draw distorted directions of the tracking path instead a straight line in Fig. 4(c) and Fig. 4(d). LPF-KF in Fig. 4(d) provides a straight line across the office, which is a promising result. This means that, LPF-KF is suitable to be applied in a narrow space with high noise because the target moves with a constant speed without many changes within typical boundaries in indoor environment. LPF-KF joins the AF, LPF and KF together, which is suitable to be applied in a narrow and close field. The difference between the three schemes are summarized in Table I.

VI. Conclusion

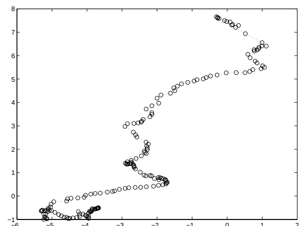
Ranging devices often suffer measurement noise and errors due to multi-path and non-line-of-sight indoor environment,



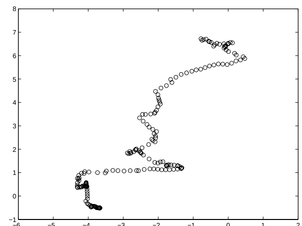
(a) The raw positions without any filter



(b) The positions processed with VF-KF

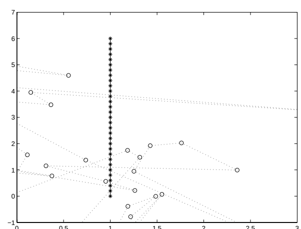


(c) The positions processed with AF-KF

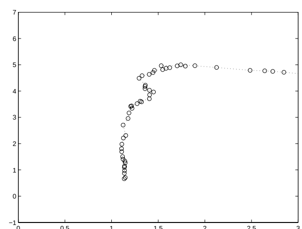


(d) The positions processed with LPF-KF

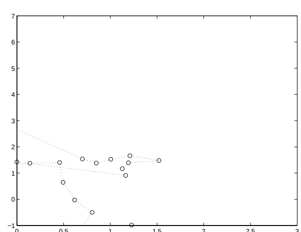
Fig. 3. Indoor Experiment I: Building Corridor with wide 1.85m and long 6.33m



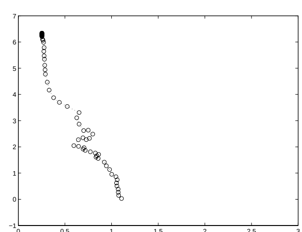
(a) The raw positions without any filter



(b) The positions processed with VF-KF



(c) The positions processed with AF-KF



(d) The positions processed with LPF-KF

Fig. 4. Indoor Experiment II: Office with wide 2.65m and long 5.60m

which cause errors in position decisions. We set up a Kalman filter model which is used to track the target with low and constant speed. To reduce indoor noise and strengthen the robustness, we use a positioning architecture with a measurement component, a pre-processing component and a data-processing component. In the pre-processing component, VF-KF and AF-KF schemes are introduced to smooth the noisy data and adapt the link failure or changing wireless environment. To further correct the positions, we also develop LPF-KF scheme for data-processing component. We set up experiments both in realistic outdoor and indoor environments to analyze the performance. Experimental results show their capabilities to process the data with noise. LPF-KF is a promising scheme for indoor tracking according to the results. Future work focus on improving the scheme and performance, testing the schemes in different scenarios and implement the schemes for real-time monitoring.

TABLE I
COMPARISON OF THREE SCHEMES

Scheme	Algorithm Complexity	Noise Reduction	Robustness
VF-KF	Complex	Medium	Medium
AF-KF	Simple	Medium	Weak
LPF-KF	Complex	Strong	Strong

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