Reliable Personnel Positioning in Industrial Environments Based on Improved Adaptive EKF With Random Packet Loss

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Abstract. In the complex industrial environment, random packet loss may occur in the process of sensor data transmission. The traditional Extended Kalman Filter (EKF) algorithm will reduce the estimation accuracy, even lead to the divergence of the estimator. To solve these problems, an improved adaptive extended Kalman filter (IAEKF) is proposed to estimate the covariance matrix of process noise adaptively. At the same time, the forgetting factor of strong tracking filter (STF) is introduced to improve the robustness of the algorithm in the case of random packet loss. Simulation results show that IAEKF algorithm can effectively reduce the personnel positioning error in the case of random packet loss, and has better localization accuracy, meeting the requirements of industrial environment.

Keywords: Improved adaptive extended Kalman filter, Personnel positioning, Random packet loss, State estimation.

1. Introduction
The complexity of industrial environment has a very important impact on personnel positioning [1-4]. At present, there are many problems in industrial, such as poor monitoring, low positioning accuracy and so on. In the industrial field, industrial personnel need to be monitored through the distance relationship between sensors and the location identification card carried by the personnel [5,6]. Therefore, the location information of wireless sensor is of great significance[6].

Wireless sensor networks (WSNs) are one of the most widely used positioning technologies in industry [7-13]. It is highly valued by industry and plays a significant role in improving production conditions. A large number of micro-sensor nodes are deployed in the monitoring area to form a multi-hop ad-hoc network system through wireless communication [8,11]. WSNs have the advantages of flexible deployment, low power consumption, small capacity and wide application range, but it is also...
affected by the battery capacity, computing power and communication bandwidth [9]. Research shows that WSNs are not restricted by wiring in industrial network, and can be effectively controlled. Therefore, the difficulty of system installation and maintenance is reduced [10]. However, random packet loss may occur during sensor data transmission. In the case of random packet loss, accurate estimation is a hot topic for scholars at home and abroad [11]. In [12], the problem of state estimation for nonlinear systems with Bernoulli measure packet loss has been studied. Based on the observation data provided by unreliable sensor networks, a new EKF algorithm has been proposed to improve the stability of the system.

In the actual industrial environment, filtering algorithm is usually used for state estimation, which has experienced the development from linear filtering to nonlinear filtering algorithm. Kalman filter (KF) is the most widely used filtering algorithm in linear system [13,14]. In [14], an adaptive KF has been proposed to reduce the positioning error. However, KF has limitations in dealing with nonlinear problems. For Industrial personnel positioning system with WSNs, state estimation can be regarded as a nonlinear filtering problem in essence. Extended Kalman filter (EKF) is usually used for nonlinear state estimation [15-20]. EKF is based on the first-order Taylor series expansion of the nonlinear function [16]. The nonlinear system is approximated to a linear system, and then treated with KF [17]. In [18], EKF has been proposed to be used in dynamic positioning system. However, EKF algorithm ignores the high-order term, which will cause errors in the process of linearization. Traditional EKF algorithm is prone to inaccurate noise covariance, which limits its application in industrial environment. In [19], in order to reduce the influence of noise, an adaptive EKF algorithm has been proposed by combining Sage-Husa adaptive filter with EKF. It effectively solves the problem that the noise covariance is not accurate or unknown. In [20], a new adaptive EKF algorithm has been proposed. Based on the online expectation maximization method, the prediction error covariance matrix and the measurement noise covariance matrix are estimated adaptively. However, in the case of random packet loss of sensor data, the above methods have limitations and the effect is not obvious.

Based on the above analysis, an improved adaptive extended Kalman filter (IAEKF) based on random packet loss is proposed for industrial environment. In order to improve the positioning accuracy, IAEKF is used to process the sensor data, and forgetting factor is introduced to improve the robustness of the algorithm to ensure the accuracy of personnel positioning.

2. Problem formulation
In this paper, the constant velocity(CV) model of three-dimensional (3D) personnel positioning system in industrial environment is studied. Figure 1 shows the sensor distribution and personnel movement trajectory in the industrial environment. Supposing that there are \( m \) sensor nodes in the multi-sensor network system, the sensor nodes identify the location identification card carried by personnel and collect location information.

![Figure 1. Sensor distribution and industrial personnel movement trajectory.](image-url)
The system model is described as follows:

$$x_{k+1} = F_k x_k + G_k \omega_k$$

$$F_k = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad G_k = \begin{bmatrix} T^2/2 & 0 & 0 \\ T & 0 & 0 \\ R^2/2 & 0 \\ 0 & T & 0 \\ 0 & 0 & T^2/2 \\ 0 & 0 & 0 & T \end{bmatrix}$$

(1)

Where $x_k = [x_{p,k}, \tilde{x}_{v,k}, y_{p,k}, \tilde{y}_{v,k}, z_{p,k}, \tilde{z}_{v,k}]$ is the state vector at time $k$. $x_{p,k}$, $y_{p,k}$, and $z_{p,k}$ are the locations of the personnel on the $x$, $y$ and $z$ axis, respectively; $\tilde{x}_{v,k}$, $\tilde{y}_{v,k}$, and $\tilde{z}_{v,k}$ are the velocity of the personnel on the $x$, $y$, and $z$ axis, respectively; $F_k$ and $G_k$ are known matrices of appropriate dimensions, respectively; $\omega_k$ is a white Gaussian random variable with zero mean values, $\omega_k = [\omega_{x,k}, \omega_{y,k}, \omega_{z,k}]^T$. The sensing model of the $i$th node is described by:

$$y_{k,i} = h(x_{k,i}) + v_{k,i}, i = 1, 2, \ldots, m$$

(3)

Where $y_{k,i} \in \mathbb{R}^m$ is the measurement of the $i$th sensor at time $k$. $h(x_{k,i})$ represents the nonlinear measurement function expression, as follows:

$$h(x_{k,i}) = \sqrt{(x_{p,k} - p_{x,i})^2 + (y_{p,k} - p_{y,i})^2 + (z_{p,k} - p_{z,i})^2}$$

(4)

Where $p_{x,i}, p_{y,i}$ and $p_{z,i}$ are the position components of the $i$th sensor node in the $x$, $y$, and $z$ axis, respectively. The process noise $\omega_k \in \mathbb{R}^n$ and the $i$th measurement noise $v_{k,i} \in \mathbb{R}^m$ are assumed to be mutually uncorrelated zero-mean Gaussian white noise sequences with the respective covariance matrices $Q_k \in \mathbb{R}^{n \times n}$ and $R_{k,i} \in \mathbb{R}^{m \times m}$. Initial state $x_0$, $\omega_k$ and $v_{k,i}$ satisfy the following statistical characteristics:

$$E(x_0) = \tilde{x}_0$$

$$E\left[ (x_0 - \tilde{x}_0)(x_0 - \tilde{x}_0)^T \right] = \tilde{P}_0$$

$$E[\omega_k v_{k,i}^T] = 0$$

(5)

In the industrial wireless network environment, there may be random packet loss in the transmission of measurement data. Therefore, considering the random packet transmission failure, the measurement equation (3) can be modified as follows:

$$\hat{y}_{k,i} = \begin{cases} y_{k,i}, & \text{The packet is received successfully} \\ y_{(k-1),i}, & \text{Otherwise} \end{cases}$$

(6)

In order to represent the problem of random packet loss more accurately, the random variable $y_{k,i} \in [0,1]$ can be introduced to describe the arrival or loss of measurement data packet at time $k$. If $y_{k,i} = 1$, it means that the measurement data at time $k$ is successfully received; otherwise, if $y_{k,i} = 0$, it means that
the measurement data is not successfully received, that is, data packet loss occurs in the transmission channel 0, and 1 are called channel failure state and normal state respectively.

\[ \hat{y}_{k,i} = y_{k,i}y_{k,i} + (1 - y_{k,i})y_{(k-1),i} \]  

(7)

When the data packet is lost, we use the measured value of the previous time to ensure the normal estimation. The nonlinear model considering random packet loss can be expressed as follows:

\[
\begin{aligned}
    x_{k+1} &= F_kx_k + G_k\omega_k \\
    \hat{y}_{k,i} &= y_{k,i}y_{k,i} + (1 - y_{k,i})y_{(k-1),i}
\end{aligned}
\]  

(8)

3. Improved adaptive extended kalman filter in case of random packet loss

3.1. Adaptive Extended Kalman filter

Adaptive extended Kalman filter (AEKF) is an adaptive estimation of process noise covariance matrix based on EKF to improve the robustness of localization. AEKF algorithm mainly includes setting initial parameters, state prediction and process update. As follows:

1) The initial state \( \hat{x}_0 \) and the error covariance matrix \( \hat{P}_0 \)
2) State Prediction
   Calculate one-step prediction estimation and one-step prediction error covariance matrix.
   \[
   \hat{x}_{k+1/k,i} = F_k\hat{x}_{k/k,i}
   \]  
   (9)

   \[
   P_{k+1/k,i}^{xx} = F_kP_{k/k,i}F_k^T + G_k\hat{Q}_kG_k^T
   \]  
   (10)

   \[
   \xi_{k+1/k,i} = \hat{y}_{k+1,i} - h(\hat{x}_{k+1/k,i})
   \]  
   (11)

   Where \( \hat{x}_{k+1/k,i} \) and \( P_{k+1/k,i}^{xx} \) represent the estimated value and the estimated error covariance of the system at time \( k \), respectively; \( \xi_{k+1/k,i} \) denotes measurement innovation vector.

   The state model of industrial personnel positioning system considered in this paper is a linear equation, so it is not necessary to linearize the state transition matrix. If the state model is a nonlinear equation, it is necessary to find the Jacobian matrix to get the state transition matrix.

3) Process update
   The measurement model of in industrial personnel positioning system is a nonlinear equation, which needs to be linearized. The linearized measurement matrix is defined as the Jacobian matrix of the following formula:

   \[
   H_{k+1,i} = \frac{\partial h}{\partial x} |_{x=\hat{x}_{k+1/k,i}}
   \]  
   (12)

   Where \( H_{k+1,i} \) is the Jacobi matrix of the measurement function.
   Calculate the covariance of the predicted measurement.
   \[
   P_{k+1/k,i}^{yy} = H_{k+1,i}P_{k+1/k,i}^{xx}H_{k+1,i}^T + \hat{R}_{k+1,i}
   \]  
   (13)

   Where \( \hat{R}_{k+1,i} \) is the estimated measurement noise covariance matrix.
   Calculate the AEKF gain, state estimation and estimation error covariance matrix.
\[ K_{k+1,i} = P_{k+1/k,i}^{xx} H_{k+1,k}^T \times \left( P_{k+1/k,i}^{yy} \right)^{-1} \] (14)

\[ \hat{x}_{k+1/k+1,i} = \hat{x}_{k+1/k,i} + K_{k+1,i} \hat{z}_{k+1/k,i} \] (15)

\[ P_{k+1/k+1,i} = [I - K_{k+1,i} H_{k+1,k,i}] P_{k+1/k,i}^{xx} \] (16)

For better on-line estimation, \( Q_k \) and \( R_{k+1,i} \) are replaced by \( \hat{Q}_k \) and \( \hat{R}_{k+1,i} \) of AEKF respectively [16], and the latter uses noise statistical estimator for adaptive estimation. The estimation of process noise covariance matrix is as follows:

\[ \hat{Q}_{k+1} = (1 - \delta_Q) \hat{Q}_k + \delta_Q diag[\theta_{k+1/k,i} \theta_{k+1/k,i}^T] \] (17)

\[ \theta_{k+1/k,i} = \hat{x}_{k+1/k+1,i} - \hat{x}_{k+1/k,i} \] (18)

Where \( \hat{Q}_0 = Q_0 \), \( \hat{Q}_{k+1} \) and \( \hat{Q}_k \) are the covariance matrices of the process noise of the next step and the current step, respectively; \( \theta_{k+1/k,i} \) is the state innovation vector based on prior and posterior estimation of the state vector; \( \delta_Q \) is a small positive value, \( 0 < \delta_Q < 1 \).

Similarly, the estimation of measurement noise covariance matrix is as follows:

\[ \hat{R}_{k+1,i} = (1 - \delta_R) \hat{R}_{k,i} + \delta_R diag[\hat{z}_{k+1/k,i} \hat{z}_{k+1/k,i}^T] \] (19)

Where \( \hat{R}_{k+1,i} \) and \( \hat{R}_{k,i} \) are the covariance matrices of the measurement noise of the next step and the current step, respectively; \( \delta_R \) is a small positive value, \( 0 < \delta_R < 1 \).

Considering that the system model assumed by the filter may not be very close to the actual physical model, the adaptation of the \( \hat{R}_{k+1,i} \) matrix is not included on account of stability concerns.

3.2. Improved adaptive extended Kalman filter

The goal of personnel positioning in industrial environment is to ensure stable positioning and high accuracy. AEKF algorithm is easy to cause divergence and is very sensitive to the selection of initial conditions. Therefore, this paper introduces STF technology based on AEKF algorithm, and modifies the one-step prediction error covariance matrix online through fading factor, so that the algorithm has the ability to deal with the scene changes and other uncertainties, and enhances the robustness of the algorithm. The flow chart of IAEKF algorithm is shown in Fig.2.

\[ \hat{P}_{k+1/k,i}^{xx} = \pi_{k+1,i} P_{k+1/k,i}^{xx} \] (20)

Where \( \pi_{k+1,i} \) represents the time-varying forgetting factor. The forgetting factors may be orthogonal to each other based on the error vectors, as follows:

\[ \pi_{k+1,i} = \begin{cases} \bar{\pi}_{k+1,i} \bar{\pi}_{k+1,i} & > 1 \\ 1, \bar{\pi}_{k+1,i} & \leq 1 \end{cases} \] (21)

\[ \bar{\pi}_{k+1,i} = \frac{\text{tr}\left[ \Psi_{k+1,i} - \hat{H}_{k+1,i} \hat{Q}_k \hat{H}_{k+1,i}^T \right]}{\text{tr}\left[ \hat{H}_{k+1,i} \hat{Q}_k \hat{H}_{k+1,i}^T \right]} \] (22)
Where $tr[]$ is the trace of the matrix; $\Psi_{k+1,i}$ is residual covariance as follows:

$$
\Psi_{k+1,i} = \begin{cases} 
\Sigma_{Z/1,i}^T \Sigma_{Z/1,i}, & k = 1 \\
\rho \Psi_{k,i} + \Sigma_{k+1/1,i}^T \Sigma_{k+1/1,i}, & k > 1
\end{cases}
$$

(23)

Where $\rho$ is forgetting factor, $0 < \rho < 1$.

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**Figure. 2** Flow charts of IAEKF algorithm

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4. Simulation and analysis
In order to verify the effectiveness of IAEKF in the case of random packet loss, Figure. 3 shows the real trajectory of personnel movement in MATLAB simulation environment.
Figure. 3 The real trajectory of personnel movement

In this paper, initial value setting of process noise covariance matrix is set as $Q_0 = 10^{-3} \times \text{diag}(2,2,2)$. Measurement noise covariance matrix is set as $R_{k,i}=1$. The simulation results are shown in Fig. 3-6. Root mean square error (RMSE) is defined as.

$$RMSE_k = \left[ \frac{1}{N} \sum_{j=1}^{N} (x_{j,k} - \hat{x}_{j,k})^2 \right]^\frac{1}{2}$$  \hspace{1cm} (24)

Where $N$ is the number of Monte Carlo simulations, which is set to 30 in this paper. Assuming that sampling period $T=1$, and initial position coordinate of industrial personnel is $(0,4,0)$. WSNs are deployed in 3D space with a length of 50 meters, a width of 5 meters and a height of 2 meters. The distribution of sensor nodes is shown in Figure. 4.

Figure. 4 Sensor Node distribution
Figure. 5 Comparison of EKF, AEKF and IAEKF without packet loss

Figure. 5 shows the comparison of EKF, AEKF and IAEKF. It can be seen from the figure that IAEKF is closer to the real trajectory with the smallest error and the highest accuracy. In the case of no packet loss, the accuracy and effect of AEKF and IAEKF are obvious. It can realize real-time, stable and accurate positioning of personnel in industrial environment.

Figure. 6 Comparison of EKF, AEKF and IAEKF in case of packet loss

Figure. 6 shows the comparison of EKF, AEKF and IAEKF in case of packet loss. It can be seen from the figure that compared with EKF and AEKF, the accuracy of IAEKF algorithm is higher, closer to the real value, and the effect is more obvious.

5. Conclusions
This paper proposed an IAEKF algorithm based on random packet loss. In order to improve the positioning accuracy, IAEKF was used to process the sensor data. The covariance matrix of state noise was estimated adaptively to improve the estimation accuracy. In the process of state estimation error covariance calculation, the forgetting factor of strong tracking filter was introduced to improve the robustness of the algorithm in the case of packet loss. Simulation results show that the algorithm can significantly improve the accuracy and robustness of personnel location in industrial environment, and the positioning accuracy of IAEKF is higher than AEKF and EKF, which meets the requirements of industrial environment.
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