Research on Combined Location Method of Dual Rail Inspection Vehicle Based on Adaptive Kalman Filter

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Abstract. Dual rail inspection vehicle has the function of inspecting rail defect points automatically and an odometer is required for its localization. Since real-time localization of rail defect points still needs manual calibration, it cannot meet the requirements of automatic vehicle operation. In this paper, the automatic localization methods are discussed. The Adaptive Kalman Filter (AKF) is employed for the multi-sensor data fusion of the odometer and the Global Navigation Satellite System (GNSS). Then the GNSS/odometer combined localization model has been built to improve the accuracy and reliability of the inspection vehicle localization. In addition, the hardware board is designed. Finally, the on-line test has been performed on the Shanghai-Hangzhou railway line. The experimental results show that our combined localization method can significantly improve the accuracy compared with that of the single GNSS method from 1.848m to 1.093m.

1. Introduction

Chinese railway transportation has entered a high-speed development era. With the railway inspection density increasing, the original railway inspection equipment needs to meet new requirements in order to ensure railway safety⁵¹. So far, two kinds of railway inspection equipment are used in China, namely manual rail detector and large detecting train. Inspecting the railway with the former equipment is inefficient and stressful. In addition, using the latter equipment on a massive scale is costly despite the fact that it can achieve high efficiency⁵². Comparing with the equipment presented above, the dual rail inspection vehicle⁵³, a new generation of railway inspection equipment, has the characteristics of lightweight, modularization and rationalization. Presently, the inspection vehicle is able to inspect rail defect points automatically and can be localized by using an odometer, one of relative localization methods, which has inevitable accumulated error, and thus needing manual calibration. Therefore, it is necessary to research precise automatic localization methods for the sake of working efficiency.

Global Navigation Satellite System, Radiolocation, Proximity and Dead Reckoning are major technologies for rail track vehicle location systems⁵⁴. Extensive related equipment is needed when applying Radiolocation or Proximity technology while it is unrealistic for the inspection vehicle. The problem of Dead Reckoning which is based on odometer has mentioned above. Applying GNSS is a feasible way to realize automatic localization of the inspection vehicle. However, it is difficult to obtain continuous localization since the satellite signal may be lost and corrupted due to high buildings, tunnels and mountains, and bad weather conditions⁵⁵. Obviously, there are limitations when only applying GNSS or using odometer, making it hard to meet the localization requirements. Multi-sensor information fusion technology sheds light on this problem. Many researches have used this technology to achieve accurate and continuous localization or navigation⁵⁶-⁵⁷.
There are many methods to realize data fusion: Weighted Averages, Bayesian Estimation, Kalman Filter, Production Rule and Artificial Neuron Net. Kalman Filter (KF) is the most common fusion algorithm used for integrating positioning approaches\cite{11}. Its design principle comes from the estimation of minimum linear equation\cite{12}. However, most of the reality problems are composed of nonlinear and time-varying system\cite{13} and in order to apply the KF to non-linear systems, the extended Kalman filter (EKF) has been developed\cite{14}. Like the KF, the EKF needs to know the noise statistical characteristics of the target system before using, but the external environment is unknown and changeable in many systems, which may cause filter divergence or accuracy degradation\cite{15-16}. To solve this problem, we need to determine the current situation of the system and then use some methods to control the filtering process through adaptive way.

Now the major approaches applied by adaptive Kalman filtering (AKF) technology\cite{17} are adaptive fading Kalman filter (AFKF), multiple model adaptive estimation (MMAE) and innovation adaptive estimation (IAE). The AFKF is to scale noise covariance matrix by multiplying a time-varying fading factor\cite{18}. The MMAE method is to select the best state estimate from the multi model Kalman filter\cite{19}. The IAE approach can judge and adjust the filter by using innovation\cite{20}. Based on this, some modified adaptive Kalman filtering approaches were designed\cite{21-24}. Bin\cite{25} proposed a method of on-line innovation adaptive adjustment of KF gain matrix, which can adjust measurement noise adaptively by creating innovation sequence and taking a limited length of sliding window sampling interval but cannot adjust the process noise. On the contrary, Wang\cite{26} proposed a new AKF approach, assuming the measurement noise to be perfectly known and focusing on the process noise. In this paper, two methods are combined to adjust both process noise and measurement noise adaptively.

This paper presents a new GNSS/odometer combined localization method based on AKF, which can calibrate and update the localization coordinates in real time, so as to compensate the GNSS unstable state and correct the odometer accumulated error periodically. Moreover, the noise covariance matrix in the fusion algorithm is adaptively processed based on IAE and proportional control, and a combined localization model has been built to improve the accuracy and robustness of the KF when the GNSS observation changes. Finally, the combined localization system has been tested to verify the method and theory proposed in this paper on the Shanghai-Hangzhou line in Songjiang District, Shanghai, China.

2. The New Adaptive Kalman Filter Algorithm

2.1. The Extended Kalman Filter Algorithm

The EKF is to use the first-order Taylor formula to expand the formula based on the idea of differentiation, transforming the nonlinear function into linear condition in a short interval to apply filtering estimation.

For the nonlinear system, the specific process of EKF are described from equation (1) to equation (6).

\[
X(k|k-1) = f(X(k-1)) + \nu(k) \tag{1}
\]

\[
P(k \mid k-1) = F(k)P(k-1)F(k)^T + Q \tag{2}
\]

\[
Z(k) = h(X(k)) + \nu(k) \tag{3}
\]

\[
K(k) = P(k \mid k-1)H(k)^T(H(k)P(k \mid k-1)H(k)^T + R)^{-1} \tag{4}
\]

\[
X(k) = X(k \mid k-1) + K(k)(Z(k) - h(X(k \mid k-1))) \tag{5}
\]

\[
P(k) = P(k \mid k-1) - K(k)H(k)P(k \mid k-1) \tag{6}
\]

where \( k \) is the current time, \( X \) is the system state description matrix, \( f \) is the state transfer equation from the previous moment to the next, \( h \) is the measurement transfer equation, \( \phi \) and \( H \) are replaced by
Jacobian matrix of nonlinear equations $f$ and $h$, $w$ is the system process noise with covariance $Q$ and $v$ is the measurement noise with covariance $R$.

### 2.2. The Adaptive Algorithm

The EKF can solve the nonlinear problem, but its basic process is still based on the standard KF whose $Q$ and $R$ needs to be determined in advance. Commonly, $Q$ and $R$ are approximated by the statistical characteristics of correlation noise in the system environment. But in the actual process, the system environment may be complex and changeable making it difficult to ensure the accuracy of statistical characteristics. Therefore, the noise covariance matrix in the filtering equation should no longer be set as the fixed value obtained by pre statistics, but be adjusted in an adaptive way.

For the process noise covariance matrix $Q$, a method of random sequence after proportional control is used to adjust it. The conventional covariance propagation steps equation (2) and equation (6) are removed in the new method and replaced by the newly elaborated propagation scheme as equation (7) and equation (8).

$$\hat{P}(k|k-1) = \hat{P}(k-1|k-2) + g\Delta\hat{P}(k), 1 \leq g < k_0 \leq k$$  \hspace{1cm} (7)

$$\Delta\hat{P}(k) = (\Delta\hat{x}(k-1)\Delta\hat{x}(k-1)^T - K(k-1)H\hat{P}(k-1|k-2)) / (k-1)$$  \hspace{1cm} (8)

where $\hat{P}(k|k-1)$ stands for the estimated one for the unknown parameter $P(k|k-1)$, $\Delta\hat{P}(k)$ denotes the feedback correction term, $g$ is a scale factor and its specific value is shown in [26], $k_0$ is the start instant, $K(k-1)$ is the Kalman gain at last moment, $\Delta\hat{x}(k-1)$ represents the posterior sequence vector calculated as equation (9).

$$\Delta\hat{x}(k) = X(k) - X(k|k-1)$$  \hspace{1cm} (9)

For the measurement noise covariance matrix $R$, the innovation sequence is used to rewrite the Kalman gain formula equation (4), so as to adjust the measurement noise adaptively. The innovation is defined as equation (10). The innovation variance is described by equation (11).

$$e(k) = Z(k) - h(X(k|k-1))$$  \hspace{1cm} (10)

$$C(k) = H(k)P(k|k-1)H(k)^T + R(k)$$  \hspace{1cm} (11)

Taking $n$ number of innovations before $k$ time, the estimated value of the innovation covariance can be described by equation (12).

$$\hat{C}(k) = \frac{1}{n} \sum_{j=k-n}^{k} e(j)e(j)^T$$  \hspace{1cm} (12)

In order to reduce the calculation amount in the process of the algorithm, the recursive expression can be described by equation (13).

$$\hat{C}(k) = \hat{C}(k-1) + \frac{1}{n}(e(k)e(k)^T - e(k-n)e(k-n)^T)$$  \hspace{1cm} (13)

It has been proved in [25] that $\hat{C}(k)$ is the maximum likelihood optimal estimation of $C(k)$, so $C(k)$ can be substituted for $\hat{C}(k)$ and then substituting into equation (4). The adaptive Kalman gain is described by equation (14).

$$K(k) = P(k|k-1)H(k)^T \hat{C}(k)^{-1}$$  \hspace{1cm} (14)
So far, equation (2) and equation (4) in the EKF process have been adaptively adjusted and replaced by equation (7) and equation (14) respectively.

3. Combined Localization System Model

3.1. Combined Localization System Overview
The AKF algorithm has been given in the last chapter and the combined localization system model will be designed in this chapter. According to the characteristics of GNSS and odometer, the odometer localization model can be put into the prediction model and the GNSS localization model can be put into the observation model. Then the combined localization algorithm framework can be obtained as shown in figure 1. Next, the specific prediction model and observation model can be built.

The pose vector of the inspection vehicle is defined as equation (15).

\[
X(k) = [x_k, y_k, \theta_k]^T
\]  

(15)

The prediction equation of the pose vector is described by equation (16).

\[
X(k|k-1) = f(X(k-1),u(k)) = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} + \begin{bmatrix} \Delta S_k \sin \theta_{k-1} \\ \Delta S_k \cos \theta_{k-1} \\ \Delta \theta_k \end{bmatrix}
\]  

(16)

where \(X(k|k-1)\) is the prior estimate of the pose vector at time \(k\), \(X(k-1)\) is the posteriori estimate of the pose vector at last time, \(\theta_k\) is the course over the ground based on true north direction, \(u(k) = (\Delta S_k, \Delta \theta_k)\) is the dynamic mileage input, which stands for the distance traveled and angle offset by the vehicle from time \(k-1\) to time \(k\). Define \(F(k)\) as the Jacobian matrix of system function \(f(X,u)\) about state vector \(X\) as equation (17).

\[
F(k) = \frac{\partial f(X,u)}{\partial X} |_{X=X(k-1),u=u(k)} = \begin{bmatrix} 1 & 0 & \Delta S_k \cos \theta_{k-1} \\ 0 & 1 & -\Delta S_k \sin \theta_{k-1} \\ 0 & 0 & 1 \end{bmatrix}
\]  

(17)
3.3. The System Measurement Model

The measurement model is built by the GNSS localization system. At time \( k \), the relationship between the observation \( Z(k) \) measured directly by GNSS and the location vector \( X \) is described by equation (18).

\[
Z(k) = h(X(k)) = \begin{bmatrix} x_{\text{gnss},k} \\ y_{\text{gnss},k} \\ \theta_{\text{gnss},k} \end{bmatrix}
\] (18)

The Jacobian matrix of the measurement transfer equation \( h \) about the location vector \( X \) is described by equation (19).

\[
H(k) = \frac{\partial h(X)}{\partial X} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\] (19)

4. Testing and Analysis

In order to verify the effect of the fusion localization algorithm, a combined localization system is designed and developed. Figure 3 shows the overall framework of the system, and figure 4 shows the entity equipment diagram. The system mainly includes a vehicle, a central processing module, a localization module, a communication module and a remote monitoring platform. The vehicle is the dual rail inspection vehicle developed by Shanghai Oriental Maritime Affairs Engineering Technology Co., Ltd. The central processing module is the Raspberry Pi 3b. The localization module is the GNSS L76 developed by QUELTEL. The communication module is the Huawei ME909S-821. The remote monitoring platform is the interface operation software developed on QT platform based on C#. The adaptive fusion algorithm is put into the software which can output single GNSS localization data and combined localization data respectively.

Figure 3. Localization system general framework

Figure 4. Localization system physical device

An experiment was performed to test the proposed adaptive fusion algorithm. During the test, a dual rail inspection vehicle was operating on the Shanghai-Hangzhou railway section in Songjiang District of Shanghai. The total length of the test section is about 6.4km. The average speed is 8m/s and the total time is 800s. Selecting part of the testing length (800m) with uniform speed (8m/s) and adopting \( T=0.5s \) as sampling period, a group of location data was obtained when the dual rail inspection vehicle was operating. The accuracy of odometer and GNSS in the combined positioning system are 1.5% and less than 2.5m CEP respectively. However, in the actual test process, it is found that GNSS is vulnerable to the interference of outdoor environmental factors making the localization accuracy unstable. The location data obtained by GNSS was put into KF as the measurement to get the optimal error estimation. Figure 5 shows the GNSS localization points selected for this test.

Firstly, the selected GNSS localization points are fitted to get the reference track of the inspection vehicle. And then the deviation degree of single GNSS localization and combined localization is
calculated based on the reference track. Finally, the comparative analysis is carried out. Figure 6 shows the reference track, the GNSS track and the combined localization track of the inspection vehicle. Figure 7 shows the deviation error comparison between GNSS localization and combined localization. It can be seen from figure 7 that compared with the single GNSS localization method, the combined localization method can effectively reduce localization error when GNSS measurement changes greatly. After the statistics of absolute location errors of all points in the two methods, we can find the maximum localization error is reduced from 6.082m to 3.092m. Meanwhile, the average localization error is reduced from 1.848m to 1.093m. The error comparison between single GNSS localization and combined localization is shown in Table 1.

| Localization method      | Maximum error (m) | Average error (m) | standard deviation |
|--------------------------|-------------------|------------------|--------------------|
| GNSS                     | 6.082             | 1.848            | 1.647              |
| Combined localization    | 3.092             | 1.093            | 0.835              |

5. Conclusion
In this paper, the localization methods for the dual rail inspection vehicle has been researched from the perspective of engineering application. And the automatic localization methods are discussed. The combined localization system has been built by the odometer and GNSS based on multi-sensor information fusion technology to realize the complementary advantages and to ensure the continuity and reliability of the automatic localization of the vehicle. The GNSS/odometer combined localization model has been built based on the fusion algorithm which is designed by the AKF. This algorithm can effectively improve the localization accuracy and the robustness. Finally, the hardware and software system of combined localization is designed and developed. And based on this, the fusion algorithm is verified by numerical simulation and experiment. The results show that combined localization system can make up for the lack of single GNSS localization accuracy and reduce localization error as well as improve stability. This algorithm provides a reliable localization method and a reliable field application scheme for railway automatic inspection.
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