Research on the Track Level Measurement Based on Multi-Sensor Information Fusion

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Abstract — The track level measurement based on multi-sensor information fusion is studied. The Kalman filter and weighted fusion estimation algorithm is used to fuse the angle sensor and the measurement data of MEMS gyroscope. It can be seen that the experimental data of the weighted fusion is more close to the real value of the MEMS gyroscope, and the random drift of MEMS gyroscope is reduced to a certain extent.

Keywords — track level measurement; multi-sensor information fusion; Kalman filter.

I. INTRODUCTION

Tow meth of Track Alignment Irregularity Detecting has two methods, the mid-cord offset method and inertial benchmark method, which are applied to inspecting cars widely. The two methods possess some obvious disadvantage: the data obtained is not much accurate and its Repeatability is not high. At present, the most of railway check instrument is just only used to check railway that has been builder, but it can’t be used when building railway. As the technique of Ballasted Track has been introduced into China, the railway check instrument cannot be meeting the need of the checking railway, building railway and alignment irregularity detecting.

Li’s [1] paper introduced Key technique of Un-ballasted Track. It innovatively used the total station as a sensor to detect the track exterior geometry condition. And it fused with technology of track alignment irregularity detecting interior geometry condition. It can complete surveying railway highly efficiently and accurately. It consists of total station, MCU system, PC manage, analyses system and others parts. The hardware of GJY-H4 inherited and improved to adapting 3D railway surveying for the system. In software, it had improved the arithmetical precision of the free station. It had built the arithmetical model of railway track surveying. It realized measure data collected manage and alignment irregularity detecting of 300m wave. The detecting system has high precision, high speed, working guide and real-time analyses, and so on. The researching findings of this paper has applied to engineering, and has great contributes to construction of China Railway High-speed and Un-ballasted Track surveying.

When engineering depot workers finished the line maintenance, they use the manual line-pulling method to verify whether the tracks after maintenance meet the requirements. With the improvement of the railway running speed, skylight time is getting shorter and shorter for the line maintenance used by engineering depot workers, so the original manual detection methods cannot meet the requirements of line inspection. The portable track detection trolleys can significantly improve the detection efficiency of the railway workers and reduce labor intensity. Therefore, using the portable track detection trolleys for line routine detection becomes the trend of line maintenance.

According to the Railway Ministry line maintenance rules and portable track inspection equipment design specifications, a track geometry parameter measurement scheme based on the principle of inertial reference is proposed, which is designed for a portable track geometry detection system. Depending on GJ-5-type track integrated detection system as the prototype, system separates suspension beam and evaluates the prototype to get the portable track inspection trolley model. Portable track geometry detection system using hand-push trolley as the main structure, installs displacement meter, accelerometer, fiber optic gyroscope and rotary encoder to measure body posture information and calculate track geometry parameters.

Through the Kalman filter algorithm used for the track geometry parameters, signal is imported into the real-time computing model. System can store and display track geometric irregularity data in the current position. In order to verify the stability and reliability of the portable track geometry inspection system, a standard track platform is built in Chi’s research [2] in the experimental environment for testing. The experimental results show that the system can effectively detect the track condition and truly reflect the rail irregularity information. The track geometry sampling interval is 0.254mm and the parameter accuracy is less than ±1mm when the inspection trolley operates at the speed of 1.2-1.5m/s [3-5]. Because the inspecting length is short and test environment is different from the real environment, repeated measurements in large distance are expected to verify the experiment data [6].

II. THE FRAMEWORK OF KALMAN FILTERING

The Kalman filter is used to fuse the angle sensor and the measurement data of MEMS gyroscope. The basic principle of the fusion is completed:
Firstly, the system of the discrete control process is introduced. A linear stochastic differential equation is used to describe the whole system:

$$X(t) = AX(t-1) + BY(t) + W(t)$$ (1)

Where X(T) is the system state of T time, and the Y(T) is the control parameter of the system. In this paper, there is no external control parameter, so the value is 0. W (T) is a system process noise matrix, which can be noted as Gaussian Noise White. Its covariance is Q. In the MSIF system, A is the transfer matrix of the system, B is the control matrix, and here is 0.

The measurement value of the system is:

$$Z(t) = HX(t) + V(t)$$ (2)

Where Z(T) is a measurement matrix of two kinds of sensors, H is the measurement matrix of two kinds of sensors, V (T) is the measurement noise matrix of two kinds of sensors, and the same as the W (T) is the Gauss white noise. Its covariance is R. Now we use Q and R to estimate the system's optimal output.

Assuming that the system state is t, it can be predicted by the former system state:

$$X(t|t-1) = AX(t-1|t-1)$$ (3)

Where X (t|t-1) is the result of the last state prediction, X (t-1|t-1) is the optimal result of the last state. The covariance of the corresponding X (t|t-1) is P. So we have:

$$P(t|t-1) = AP(t-1|t-1)A^T + Q$$ (4)

Where P (t|t-1) is the covariance of X (t|t-1), and P (t-1|t-1) is the covariance of X (t-1|t-1). (4-20) and type (4-21) to express the prediction of the system. With the result of the present t, and the measurement of the t time, the optimal X (t|t) of the t time can be obtained:

$$X(t|t) = X(t|t-1) + Kg(t)(Z(t) - HX(t|t-1))$$ (5)

Where Kg(t) is the Kalman gain gain in t time.

$$Kg(t) = P(t|t-1)H^T[HPT(t|t-1)H^T + R]^{-1}$$ (6)

In order to keep the Kalman filter in operation until the end of the system, the P (t|t) X (t|t) is required to update the t moment.

$$P(t|t) = (I - Kg(t)H)P(t|t-1)$$ (7)

I is the two order unit matrix and equation (7) ensures the auto regression operation of Kalman's algorithm.

III. WEIGHTED FUSION ALGORITHM

The measurement of the same kind of multi sensor data can be seen as non-random quantity estimation from a large amount of data with noise. Because of the noise in the measurement data, the estimation error is estimated by the estimated value of these data, and the error is random. In order to reduce the real time and accuracy of measurement, it is necessary to measure the real time of the same type. In order to improve the real-time performance and accuracy of the measurement, a physical quantity is measured.

The weighted fusion estimation algorithm does not need any prior knowledge of the sensor measurement data, and only the measurement data provided by the sensor can be integrated with the least square error data fusion value. The mean square error of the estimation is not only less than the mean square error of the single sensor estimation, but the mean square error of the mean square error of the mean square error of the mean square error.

Two different sensors are measured, and the observed values are:

$$Z_1 = X + v_1$$ (8)

$$Z_2 = X + v_2$$ (9)

Where $$v_i (i=1,2)$$ is the random error of observation, and $$v_i \sim N(0, \sigma_i^2)$$, the two sensor observation values are independent of each other.

If the X's estimated value $$\hat{X}$$ is linear with the observed value $$Z_i (i=1,2)$$, and the $$\hat{X}$$ is the unbiased estimate of X, then we have:

$$\hat{X} = \omega_1 z_1 + \omega_2 z_2$$ (10)

$$\Omega = (\omega_1, \omega_2)$$ is the measurement of the value of the weight of each sensor.

Set the estimation error is:

$$\tilde{X} = X - \hat{X}$$ (11)

The cost function is A's mean square error is:

$$J = E(\tilde{X}^2) = E$$

$$\{[x - \omega_1(x+z_1) - \omega_2(x+z_2)]^2\}$$ (12)

Because the $$\hat{X}$$ is X's unbiased estimate, so:

$$E(\tilde{X}) = E(x) = E(\hat{x})$$

$$-\omega_1(x+z_1) = 0$$ (13)

Because $$E(v_i) = E(v_i) = 0$$, so we have:

$$\omega_2 = 1 - \omega_1$$ (14)

The cost function can be noted as:

$$J = E(\tilde{X}^2) = E[\omega_1^2v_1^2 + (1-\omega_1)^2v_2^2 + 2\omega_1(1-\omega_1)v_1v_2]$$ (15)

Because $$E(v_i^2) = \sigma_i^2$$, $$E(v_i) = \sigma_i^2$$, V1 V2 is depended and $$E(v_1v_2) = 0$$, so we have:

$$J = E(\tilde{X}^2) = \omega_1^2\sigma_1^2 + (1-\omega_1)^2\sigma_2^2$$ (16)

To make J gets the minimum value, we evaluate the derivation of $$\Omega$$:

$$\frac{\partial J}{\partial \Omega} = 0$$ (17)

The optimal weight value is obtained:

$$\omega_1^* = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}$$ (18)
Optimal estimation is:
\[
\hat{x} = \frac{\sigma_z^2 z_1 + \sigma_z^2 z_2}{\sigma_z^2 + \sigma_z^2} \frac{\sigma_z^2 z_1 + \sigma_z^2 z_2}{\sigma_z^2 + \sigma_z^2} \quad (20)
\]

When the value of the two sensors is appropriate, the most available estimates can be obtained by the observer. To extend this conclusion to the case of multiple sensors, the variance of multi sensor group is \( \sigma_i(i = 1, 2, \ldots) \), and the measurement value of each sensor is \( z_i(i = 1, 2, \ldots) \), which is independent of each other. The true value of the estimated value is \( x \), and it is the unbiased estimate of \( x \). The weighting factor of each sensor is \( \omega_i(i = 1, 2, \ldots) \). According to the multivariate function, the weighted factor corresponding to the minimum of the mean square error is obtained:

\[
\omega^*_i = \frac{1}{\sigma_i^2 \sum_{i=1}^{n} \frac{1}{\sigma_i^2}} \quad (21)
\]

IV. EXPERIMENT RESULT AND DATA ANALYSIS

Level irregularity is one of the most important indexes of the track irregularity. The most important and most widely used method is to use the track inspection instrument (hereinafter referred to as the rail gauge).

At present, the track gauge is used to measure the track irregularity. The sensor's core principle is usually based on accelerometer, static performance is good, and it is suitable for the slow change of information. However, due to the implementation of the track gauge in the implementation of dynamic detection, it is impossible to be a long uniform movement, while the track contains rail joints, weld, rail and other interference information, the angle of the measurement will become inaccurate, seriously affecting the track level disease diagnosis, positioning and location. Based on this situation, this paper introduces the Electro Mechanical Systems (MEMS) Multi-Source (MSIF) MEMS (Fusion), which has good dynamic characteristics of microelectronic mechanical system (Micro), which is used to measure the information of multi sensors (Information). Table 1 show the comparison of the two sensors.

The angle sensor of track level measurement system is the JEWELL's single axis force balanced servo angle sensor LCF-100. The measurement range is 15 degrees, and the output is -5V~+5V. Gyroscope for the development is a tactical level micro gyroscope STIM210 made by the Norway Sensonor. The measurement range is (250) dps/ (500) dps/ (2000) DPS which can be adjusted. Output uses SPI/I2C interface, it is very easy to connect with MCU.

Sensor is installed in a T-shaped hand push the railway inspection instrument, which tilt sensor installed in the middle position of the crossbeam of the vehicle body; MEMS gyroscope is installed in the middle position of the vehicle body side arm, sensitive direction and angle sensor is sensitive to the same direction. As shown in figure 1:

Figure 1. Schematic diagram of sensor installation

In Figure 1, 1, 2, 3 is the wheel, 4 is the angle sensor and 5 is the MEMS gyroscope.

The level is defined as the height difference between the two track top surfaces of the same track section, which is called a super high (the deviation of the normal height deviation. The horizontal irregularity will cause the vehicle to roll the rolling vibration, resulting in the side of the wheel load, the side of the wheel load reduction. North American railway experts believe that the severity of the curve is not smooth, is often an important reason for the derailment of freight cars. If the direction and level of the two kinds are different uneven, and the reverse composite, the risk of derailment is more dangerous.

The rail gauge is directly measured by the angle sensor, and is similar to the position of the horizontal instrument. The angle sensor is installed on the beam of the on orbit inspection instrument. The model is shown in Figure 2:

Figure 2. Horizontal measurement model

The measured level ultra-high \( H \) is:

\[
H = L \cdot \sin \theta \quad (22)
\]

Where \( \theta \) is the angle between the top line and the horizontal plane of the left and right track. \( L \) is center line distance of left and right track.
The rail gauge is used to measure the track level of MEMS gyroscope. The output signal is zero in the stationary state. When the attitude of the gyroscope continues to change, the output signal will be changed and the output signal of the gyroscope is denoted as:

\[ \varphi = \int \omega dt \]  

(23)

Where \( \omega \) is the angular velocity of gyro. \( \varphi \) is the angle. In the actual processing, the output value of the gyro output value of the fixed time is easy to be calculated by the microprocessor.

### TABLE 1. THE COMPARISON OF THE TWO SENSORS

<table>
<thead>
<tr>
<th>Angle sensor</th>
<th>Gyroscope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Be measured</td>
<td>Angle</td>
</tr>
<tr>
<td>Advantage</td>
<td>Angular velocity</td>
</tr>
<tr>
<td>Disadvantage</td>
<td>Dynamic response is slow, is not suitable for dynamic angle tracking</td>
</tr>
</tbody>
</table>

The basic principle of the algorithm is verified by the upper section, the main experimental steps are as follows:

First of all it needs to set the initial value of the system and the corresponding covariance to make the Kalman filter start work, now make the zero time system of the initial forecast value of X0 is 0, the X0 option can be arbitrary, because the constant work of the Kalman filter will gradually converge, but for the initial system covariance P0 cannot be 0, otherwise the system will be identified as the optimal value, so the filter cannot converge, so set:

\[ P_0 = \begin{bmatrix} 5 & 0 \\ 0 & 3 \end{bmatrix} \]

For system transfer matrix A, set:

\[ A = \begin{bmatrix} 1.005 & 0 \\ 0 & 1.05 \end{bmatrix} \]

For the system process noise covariance Q, due to the whole measurement process of the outside interference is small. Set:

\[ Q = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.01 \end{bmatrix} \]

It is assumed that the data of the angle sensor and MEMS gyroscope are reliable, that is, both the measurement parameters are set to 1, so the measurement equations of the angle sensor and MEMS sensor are respectively:

\[ Z_A(t) = X(t) + V_A(t) \]

\[ Z_B(t) = X(t) + V_B(t) \]

On the ZA(t) and ZB(t) is the measurement of the angle sensor and MEMS gyroscope X(t), VA(t) and VB(t) takes the measurement noise of the MEMS gyroscope. Taking into account the large drift of MEMS gyroscope, the RA(t) is 0.01, the measurement noise covariance MEMS RB(t) is 0.1. Then get the measurement matrix H and system measurement noise matrix R:

\[ H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \]

\[ R = \begin{bmatrix} 0.01 & 0 \\ 0 & 0.1 \end{bmatrix} \]

Based on the weighted fusion estimation algorithm, it can only be used for the measurement data of the sensor. The traditional weighted fusion algorithm is used to process the data of the angle sensor and MEMS gyroscope. The experiment result of Kalman filter and weighted fusion estimation algorithm is shown in the figure 3.

![Figure 3. The experiment result of Kalman filter and weighted fusion estimation algorithm](image)

It can be seen that the experimental data of the weighted fusion is more close to the real value of the MEMS gyroscope, and the random drift of MEMS gyroscope is reduced to a certain extent.

Mean square error of two algorithms is shown in the table 2.

### TABLE 2. MEAN SQUARE ERROR OF TWO ALGORITHMS

<table>
<thead>
<tr>
<th>Item</th>
<th>Mean square error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kalman filter</td>
<td>1.3054</td>
</tr>
<tr>
<td>Weighted fusion estimation algorithm</td>
<td>1.4175</td>
</tr>
</tbody>
</table>

### V. CONCLUSIONS

In this paper, the author studies the track level measurement based on multi-sensor information fusion. The Kalman filter and weighted fusion estimation algorithm is used to fuse the angle sensor and the measurement data of MEMS gyroscope. However, due to the implementation of the track gauge in the implementation of dynamic detection, it is impossible to be a long uniform movement, while the track contains rail joints, weld, rail and other interference information, the angle of the measurement will become inaccurate, seriously affecting the track level disease diagnosis, positioning and location. Based on this situation,
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REFERENCES