A Multi-Sensor Data Fusion Method for Navigation

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Abstract: A data fusion method based on navigation observations from multiple sensors with asynchronous sampling rates is presented aiming at the accomplishment of an optimal navigation result. Firstly, the observation estimations of navigation sensors at the same designated time are obtained through the fitting or interpolation algorithms based on the multi-sensors’ measurements at different times, which solves the observation inconsistency resulting from asynchronous sampling frequencies of multi-sensors. Secondly, the optimal navigation result is achieved through assigning appropriate weights to the above observations or estimations based on the relationships among them. Finally, the data fusion method is validated by simulation, and the results demonstrate that it can effectively reduce the observation noises of multi-sensors and improve the accuracy of navigation. Copyright © 2014 IFSA Publishing, S. L.

Keywords: Data fusion, Multi-sensor, Navigation, Fitting, Interpolation.

1. Introduction

The performance of any single navigation sensor is limited due to its own physical principles and application conditions, although it may work well in certain specific scenarios. Some different kinds of sensors can be combined together in order to make full use of their performance advantages. Thus navigation data fusion technology becomes an interesting issue for the use of multiple navigation sensors [1-4].

In recent years, despite being widely used in remote sensing and other related fields [5-6], there have ever been little data fusion methods used in navigation field, except for certain exclusively applications subjected to their own features [7]. The conflicts and redundancies of data from multiple navigation sensors remain to be solved.

In this paper, a new data fusion method is presented to solve these problems. The features of the method include:

a) Eliminating the sampling inconsistency of multi-sensors;

b) Taking redundancies into account and assigning the appropriate weights to each sensor;

c) Effectively reducing the observation noises of each sensor.

2. Data Fusion

The coordinate transformation method is not discussed in this paper and it is assumed that the coordinates are unified.

Assuming \( t \) is the starting point of observations, and \( t+1 \) is the designated fusion moment. As the sampling frequencies are different, the total number
of observations from the sensors may be varying. \(X_1, X_2, ..., X_N\) are the observation set of \(N\) sensors during \((t, t+1]\), they can be depicted as follows:

\[
X_i = \{\hat{x}_i(t + \alpha_{1i}), \hat{x}_i(t + \alpha_{2i}), ..., \hat{x}_i(t + \alpha_{Ni})\}, \quad i = 1, ..., N,
\]

where \(\alpha_{ji} \in (0, 1]\) is the different sampling moments within \(t, t+1\], \(\hat{x}_i(t + \alpha_{ji})\) identifies the \(j\)th observation of the \(i\)th sensor, \(i = 1, ..., N\), \(j = 1, ..., N_i\), \(N_i\) is the total number of the observations of the \(i\)th sensor. The dimension of observation vectors of different sensors can be variable.

In the view of observations during \((t, t+1]\) are sampled at various moments due to different sampling frequencies, we propose a data fusion method to obtain the fusion results at the time of \(t+1\).

The data fusion method is accomplished by the two processes, which are respectively, data prediction model and weighted fusion algorithm. Data prediction model is to get the estimations for a sensor at the fusion time \(t+1\), when there are no observations of the sensor. Weighted fusion algorithm is to achieve an effective fusion result for the multiple navigation sensors on the observations or the estimations at the fusion time \(t+1\).

### 2.1. Data Prediction Model

Based on the observation data within \((t, t+1]\) of some certain sensors which have no observations at \(t+1\), the function model using either orthogonal polynomial fitting or interpolation is defined to predict \(\hat{x}_i(t+1)\), \(i = 1, ..., N\), which is the estimation of the \(i\)th sensor at fusion time \(t+1\).

Since the oscillation phenomenon, called Runge, would generate, if the interpolation degree \(n\) were designed too large, and the error would be enlarged, the prediction model is selected based on the total number of observation data, and \(\text{Num}\) is a given threshold. When the total number is more than \(\text{Num}\), we select an orthogonal polynomial fitting to predict \(\hat{x}_i(t+1)\), otherwise Lagrange interpolation would be used. The function model is designated as follows to predict the estimations for the sensors:

\[
\hat{x}_i(t+1) = \begin{cases} 
\sum_{j=1}^{N} \hat{x}_i(t + \alpha_{ji}) L_{n_j}(t+1), \text{Num} \geq N_i, \\
\sum_{n=0}^{N_i} c_{n} P_m(t+1), \text{Num} > \text{Num} 
\end{cases}
\]

where \(\hat{x}_i(t + \alpha_{ji})\) is the \(j\)th observation value of the \(i\)th sensor which has no observations at \(t+1\), \(L_{n_j}(x)\) is the \(j\)th base function from Lagrange interpolation defined as

\[
L_{n_j}(t+1) = \frac{w_{n_j}(t+1)}{(1-\alpha_j) w_{n_j}(t+\alpha_j)}, \quad j = 1, 2, ..., N_i, 
\]

where \(w_{n_j}(t+\alpha_j)\) is the \(j\)th observation time of the \(i\)th sensor, \(c_{n}\) is the \(m\)th coefficient of the fitting, obtained from the following equation:

\[
c_{m} = \frac{\sum_{j=1}^{N} \omega_{\alpha + \alpha_j} \hat{x}_i(t + \alpha_{ji}) L_{n_j}(t+1) P_m(t + \alpha_j)}{\sum_{j=1}^{N} \omega_{\alpha + \alpha_j} P_m^2(t + \alpha_j)}, \quad m = 0, 1, ..., n-1. 
\]

### 2.2. Weighted Fusion Algorithm

The algorithm accomplishes the data fusion by assigning the appropriate weights to the estimations or observations of \(N\) sensors at the integer time \(t+1\), according to the spatial correlation among them. The process is shown in Fig. 1. The algorithm prototype can be seen in the Ref. [9].

The spatial correlation are expressed by \(d_{ik}\), identifying the distance among any two estimations or observations of the \(N\) sensors, and \(i, k\) refers to the \(i\)th and the \(k\)th sensor respectively. \(d_{ik}\) is presented as

\[
d_{ik} = |\hat{x}_i(t+1) - \hat{x}_k(t+1)|, \quad i, k = 1, ..., N.
\]
where $\hat{x}(t+1)$ and $\hat{x}_k(t+1)$ are the estimation result or observation of the $i^{th}$ and $k^{th}$ sensor at the integer time $t+1$. The supporting degree function $r_{ik}$, which is the element of supporting degree matrix $R=[r_{ik}]_{N\times N}$, is presented as

$$r_{ik} = \frac{d_{ik}}{\max(d_{ik})} + 1 \quad (10)$$

and the weighted matrix $W$ is

$$W = \frac{R^*L}{|R^*L|}, \quad (11)$$

where $L$ is the corresponding eigenvector of eigenvalue $\lambda$, whose absolute value is the largest in all the eigenvalues from the supporting degree matrix $R$. $W=[w_1, w_2, \ldots, w_N]^T$ is the weighted coefficient vector, and $w_i$ is the weighted value of the $i^{th}$ sensor, and the relationship among $w_i$ getting from (11) is the following:

$$\sum_{i=1}^{N} w_i = 1 \quad (12)$$

The fusion result is obtained from the following equation:

$$\hat{x}_j(t+1) = \sum_{i=1}^{N} w_i \hat{x}_i(t+1) \quad (13)$$

3. Simulation

In this section, an application scenario in which there are four navigation sensors observing the same object is used to validate the accuracy and efficiency of our multi-sensor data fusion method. To simplify the position determination process of each navigation sensor and manifest the process of data fusion method, the positions expressed by the vector of $(x, y, z)$, which is the combination of true position and noises from various models, and selected as observation data of navigation sensors. The sampling frequencies of each sensor are 500 Hz, 142.9 Hz, 10 Hz, and 2.5 Hz respectively. The time span of the whole method is $(t, t+1)$ s, that is 1 s.

The models of observation noises of each navigation sensor shown in Fig. 2 in every dimension are represented as follows:

a) Sensor I: The mean and variance of random noises distributed normally are 0 and 100 respectively.

b) Sensor II: The mean and variance of random noises distributed normally are 0 and 300 respectively.

c) Sensor III: The mean and variance of random noises distributed normally are 20 and 200 respectively.

d) Sensor IV: The mean and variance of random noises distributed normally are 10 and 500 respectively.

The true, predicted and observation positions of each sensor at integer seconds, are shown in Fig. 3, Fig. 4, Fig. 5 and Fig. 6. The true position and the position determination by our multi-sensor data

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**Fig. 1.** The process of weighted fusion algorithm.

**Fig. 2.** Noises of the four sensors at sampling moments.
fusion method are shown in Fig. 7. The statistical errors of position are shown in Table 1. To manifest the results clearly, the statistical time span is adjusted to 60 seconds, although the span is elongated, the results will remain similar.

As shown in Table 1, the root mean square (RMS) of the fusion errors is 16.6002 meters better than results of any sensors, indicating that our data fusion method can obtain the optimal position determination.

Figure 3. Comparison between the observations of sensor I and the true position at integer seconds.

Figure 4. Comparison between predictions or observations of sensor II and the true position at integer seconds.

Figure 5. Comparison between observations of sensor III and the true position at integer seconds.

Figure 6. Comparison between predictions or observations of sensor IV and the true position at integer seconds.

Figure 7. Comparison between the fusion position and the true position at integer seconds.

Table 1. The comparison of the statistical errors.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Errors of observations at all the sampling points</th>
<th>Errors of observations at integer seconds</th>
<th>Errors of predictions at integer seconds</th>
<th>Errors of multi-sensor data fusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>17.3291</td>
<td>15.2674</td>
<td>N/A</td>
<td>16.6002</td>
</tr>
<tr>
<td>II</td>
<td>30.2036</td>
<td>24.4824</td>
<td>17.2056</td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>41.8993</td>
<td>43.8363</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>44.3698</td>
<td>32.1344</td>
<td>76.7261</td>
<td></td>
</tr>
</tbody>
</table>

*N/A* indicates none predictions, i.e. there are observations at all the integer seconds for Sensor I and Sensor III.
4. Conclusions

Our data fusion method adopts a prediction model which accomplishes either by an orthogonal polynomial fitting function or interpolation to obtain the predictions at integer seconds if certain sensors do not have observations at that time, and then a weighted fusion algorithm which can acquire the optimal result on inter-dependence of observations and predictions from multiple sensors and efficiently reduce conflict and redundancy of these data.

Simulation results show it can effectively reduce effects of large errors from any single sensor, and assure the final fusion result more accurate, stable and anti-interference. Consequently, our data fusion method is efficient, practical and accurate and is applicable to the multi-sensor applications.

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References