A FUZZY LOGIC BASED MULTI-SENSOR NAVIGATION SYSTEM FOR AN UNMANNED SURFACE VEHICLE

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Abstract:
This paper investigates the implementation of three variations of fuzzy logic based Kalman filters namely centralized, decentralized and federated. These fuzzy logic adaptive Kalman filter (FLA-KF) algorithms are implemented in an unmanned surface vehicle (USV) application. Simulation results demonstrate the algorithms' capabilities under different types of sensor faults and the results are compared on the basis of accuracy, computation efficiency and fault tolerant performance.

Keywords: Unmanned Surface Vehicle (USV), Navigation, Multi-sensor data fusion (MSDF), Kalman filter, Fuzzy logic adaptive Kalman filter (FLA-KF).

1. INTRODUCTION

In an effort to reduce the cost of environmental data gathering and oceanographic research, an unmanned surface vehicle (USV) named Springer is in the process of being developed by the Marine and Industrial Dynamic Analysis (MIDAS) Research Group, University of Plymouth.

The vehicle is being designed primarily for undertaking pollutant tracking, environmental and hydrographic surveys in rivers, reservoirs, inland waterways and coastal waters, particularly where shallow waters prevail. An equally important secondary role is also envisaged for Springer as a test bed platform for other academic and scientific institutions involved in environmental data gathering, sensor and instrumentation technology, control systems engineering and power systems based on alternative energy sources. Herein, Springer hardware and software particulars are presented including various navigational sensors, speed controller and an environmental monitoring unit.

Fig. 1. Perspective of Springer

Springer USV was designed as a medium waterplane twin hull (MWATH) vessel which is versatile in terms of mission profile and payload. It is approximately 4m long and 2.3m wide with a displacement of 0.6 tonnes. The vehicle is depicted in Fig. 1.

The integrated sensor suite of Springer is shown in Fig. 2; it combines GPS, three different types of compass, a speed log and a depth sensor. All of these sensors connect to a PC via a NI-PCI...
In order for the vehicle to be capable of undertaking the kinds of mission that are contemplated, Springer requires a robust, reliable, accurate and adaptable navigation, guidance and control (NGC) system.

The navigation system is responsible for accurate and adaptable navigation, guidance and control (NGC) system.

In section 2, the multi-sensor navigation strategy is described and fuzzy logic adaptive cascaded Kalman filters (FLA-KFs) are briefly introduced. In section 3, FLA-KFs are implemented on three compasses and fault tolerant performances are investigated under different sensor faults. Finally, conclusions are presented in section 4.

2. MULTI-SENSOR NAVIGATION STRATEGY

2.1 Kalman filter

Among the various estimation algorithms available for MSDF, the Kalman filtering based approach has been applied successfully in many practical problems, particularly in navigation (Luo et al. 2002). The filter uses the statistical characteristics of a measurement model to determine estimates recursively for the fused data that are optimal in a statistical sense. If the system can be described in a linear model form, and both the system and sensor errors can be modelled as white Gaussian noise, the Kalman filter will provide unique statistically optimal estimates for the fused data (Brown and Hwang 1997).

Considering the following system:

$$z_k = H_k x_k + \nu_k$$

where $x \in \mathbb{R}^m$ is a state vector, $H \in \mathbb{R}^{n \times m}$ is an observation model, and $\nu \in \mathbb{R}^n$ is the observation noise. The state vector satisfies a linear discrete time state transition equation:

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

where $F \in \mathbb{R}^{m \times m}$ is the system model, $G \in \mathbb{R}^{m \times q}$ is the control model, $u \in \mathbb{R}^q$ is a known control input, and $\omega \in \mathbb{R}^m$ is the input noise.

The Kalman algorithm can be organized into time update and measurement update equations.

Time update equations:

$$\hat{x}_{k+1}^- = F_k \hat{x}_k + G_k u_k$$

$$P_{k+1}^- = F_k P_k F_k^T + Q_k$$

measurement update equations:

$$K_k = P_k^c H_k^T [H_k P_k^c H_k^T + R_k]^{-1}$$

$$\hat{x}_k = \hat{x}_{k+1}^- + K_k [z_k - H_k \hat{x}_k]$$

$$P_k = [I - K_k H_k] P_k^- [I - K_k H_k]^T + K_k R_k K_k^T$$

The measurement update equations incorporate a new observation into the priori estimate from the time update equations to obtain an improved posteriori estimate. In the time and measurement update equations, $\hat{x}_k$ is an estimate of the system state vector $x_k$, $K_k$ is the Kalman gain and $P_k$ is the covariance matrix of the state estimation error. The 'super minus' in the equation reminds the reader that it is a priori estimate before the measurement. The 'super plus' denotes the estimate after the measurement update.
2.2 Cascaded Kalman filter

In the literature, three main Kalman filter based MSDF architectures are suggested (Gao and Abousalem 1993): centralized Kalman filtering (CKF), decentralized Kalman filtering (DKF) and federated Kalman filtering (FKF). All the systems have their own merits and demerits. CKF based MSDF systems communicate and process all measured sensor data in a central site. The advantage of this method is that it involves minimal information loss, however, it can result in a high computational load. DKF and FKF are two stage data processing techniques which divides the standard Kalman filter into local filters and a master filter. Firstly, the local filters process their own data in parallel to yield the best possible local estimates, then the master filter fuses the local estimates to generate the best global solution. FKF takes a step further than DKF by employing information share, where it includes information feedback from the master filter to the local filters in given proportions. DKF is computationally efficient while FKF has been recognized as the best solution for fault detection and tolerance (Escamilla-Ambrosio and Mort 2004).

2.3 Fuzzy logic adaptive Kalman filter

A significant difficulty in designing a Kalman filter can often be traced to incomplete a priori knowledge of the process covariance matrix (Q) and measurement noise covariance (R). These matrices are often initially estimated from experience or are even unknown. However, it has been shown that insufficient priori knowledge can reduce the precision of estimation, or even can lead to divergence. The adaptation here is to adaptively tune the measurement noise covariance matrix to fit the actual statistic of the noise profile present in the incoming measured data. The adaptation is based on a technique known as covariance matching.

At a sample time \( k \), the innovation \( \text{Inn}_k \) is the difference between the real measurement \( z_k \) and estimated value \( \hat{z}_k \) from the filter. The actual covariance is defined as an appropriate of the \( \text{Inn}_k \) sample through averaging inside a moving estimation window of size \( M \) (Mohamed and Schwarz 1999), and it has the following form:

\[
\hat{C}_{\text{Inn}_k} = \frac{1}{M} \sum_{j=j_0}^{k} \text{Inn}_k \text{Inn}_k^T \quad (11)
\]

where \( j_0 = k - M + 1 \) is the first sample inside the window and \( M \) is chosen empirically to give some statistical smoothing (Escamilla-Ambrosio and Mort 2003). Experimental results showed that a good size for the moving window is 15.

The theoretical covariance of the innovation sequence is defined in equation 12:

\[
S_k = H_k P_k^{-1} H_k^T + R_k \quad (12)
\]

If a discrepancy is found between the actual covariance and theoretical covariance, then a fuzzy inference system (FIS) produces adjustments for the diagonal elements of \( R_k \) based on the size of this discrepancy. The discrepancy is defined by a variable called the degree of mismatch (DoM\(_k\)):

\[
\text{DoM}_k = S_k - \hat{C}_{\text{Inn}_k} \quad (13)
\]

If the actual covariance is greater than its theoretical value, the value of \( R_k \) is increased. Three fuzzy rules can be generated:

- IF DoM\(_k\) = 0 THEN \( R_k \) MAINTAIN
- IF DoM\(_k\) > 0 THEN \( R_k \) DECREASE
- IF DoM\(_k\) < 0 THEN \( R_k \) INCREASE

Therefore, the adjustment can be applied to \( R_k \):

\[
R_k = R_{k-1} + \Delta R_k \quad (14)
\]

Hence, a single input and single output (SISO) FIS is produced to adjust the element in \( R_k \). The FIS can be implemented considering three fuzzy sets for DoM\(_k\): N=Negative, Z=Zero and P=Positive. For \( \Delta R_k \), three fuzzy sets are specified: I=Increase, M=Maintain and D=Decrease. The membership functions are shown in Fig. 3.

![Fig. 3. Membership function for DoM\(_k\) and \( \Delta R_k \).](image)

2.4 An adaptive determination method for the information feedback factors

The information feedback factors (\( \beta(i) \)) in the FKF represent the unitary portion of estimation information from the local Kalman filters in the total fusion estimation. The higher the value of \( \beta(i) \), the larger the contribution made from the
local filter to the master filter at the next sampling time \((i + 1)\). In order to make the FKF adaptive with the estimation accuracies, Zhang et al. (2002) present a method to change the feedback factors on-line according to the corresponding eigenvalues of a matrix \(P\). The eigenvalues of the matrix \(P\) in the Kalman filtering equation represent the covariance of their corresponding state vectors.

In the FKF, the covariance matrix of the \(i\)th local filter \(P_i\) can be decomposed as:

\[
P_i = LΛ_iL^T
\]

where \(Λ_i = diag(λ_{i1}, λ_{i2}, \ldots, λ_{iN})\), \(λ_{i1} \sim λ_{iN}\) are the eigenvalues of \(P_i\), \(L\) is the corresponding eigenvectors matrix.

As the eigenvalues of \(P_i\) can be positive or negative, \(P_i^TP_i\) is used to replace \(P_i\) to perform the eigenvalue decomposition:

\[
P_i^TP_i = L'Λ_i'(L')^T
\]

where \(Λ_i' = diag(Λ_{i1}', Λ_{i2}', \ldots, Λ_{im}')\), and \(Λ_{ij}' = λ_{ij}', j = 1, 2, \ldots, N\).

As a result its information feedback factor values are given by:

\[
β_i = \frac{trΛ_i'}{trΛ_{1}' + trΛ_{2}' + \cdots + trΛ_{n}' + trΛ_{m}'}
\]

3. FAULT TOLERANT FEATURES UNDER DIFFERENT SENSOR FAULTS

It has been proven that multiple motion sensors play a vital role in autonomous navigation. In real situations, there is always the possibility of sensor failure, therefore, to realise reliable and robust navigation in Springer, fault detection and isolation is one of the main concerns.

At any time, a sensor may stop sending information under three kinds of sensor faults: transient, persistent or permanent (Escamilla-Ambrosio and Mort 2004). In this paper these three types of fault are defined as:

- Transient fault: the fault lasts on the sensor for 1 sampling time and then recovers to the normal operating condition.
- Persistent fault: the fault lasts on the sensor for a few sampling periods and then recovers to the normal operating condition.
- Permanent fault: the fault remains on the sensor until the sensor is isolated physically.

In any of the above cases, the navigation system must immediately identify the failed sensor and act in such a way that data from the failed sensor will not corrupt the global estimates.

In order to compare the robustness of FLA-KF algorithms, the FLA-CKF, FLA-DKF and FLA-FKF are implemented on three sets of compass measurements under transient, persistent and permanent faults separately. The accuracies of each performance are compared in Table 1 using root mean square error (RMSE) values.

3.1 Transient faults

In Figs 4 to 6, four transient faults are added on the TCM2 measurements at 100, 200, 300 and 400 second respectively. The information feedback factors in FLA-FKF are shown in Fig. 7.

From the fusion result in Fig. 4, the FLA-CKF is not robust enough to tolerate these transient faults, therefore in the following section only FLA-DKF and FLA-FKF will be implemented under sensor persistent and permanent fault conditions.
Fig. 6. FLA-FKF performance with transient faults on the TCM2

Fig. 7. Information feedback factors ($\beta_i$) under transient faults on the TCM2

3.2 Persistent faults

In Figs 8 and 9, four persistent faults are simulated on the TCM2 at times 100, 200, 300 and 400 second respectively. Fixed values are given with duration of 10 seconds. The feedback factors in FLA-FKF are shown in Fig. 10.

Fig. 8. FLA-DKF under persistent faults on the TCM2

Fig. 9. FLA-FKF with adaptive feedback factors under persistent faults on the TCM2

Fig. 10. Information feedback factors ($\beta_i$) of FLA-FKF under persistent faults on the TCM2

3.3 Permanent fault

In Figs 11 and 12, a permanent fault is added on the TCM2 from 300 second. The feedback factors of FLA-FKF are shown in Fig. 13.

Fig. 11. FLA-DKF under permanent faults on the TCM2

Fig. 12. FLA-FKF under permanent faults on the TCM2
3.4 Result analysis

From the RMSE values in Table 1, it appears that the FLA-CKF is not effective in decreasing sensor fault disturbances. The FLA-DKF is computational efficient, however the accuracy is reduced when the sensor has a permanent fault. The most accurate solution is the FLA-FKF as it can adapt different sensor fault situations without corruption to the global estimation.

Table 1. FLA-KF estimation accuracies using RMSE

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>FLA-CKF</th>
<th>FLA-DKF</th>
<th>FLA-FKF</th>
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<tbody>
<tr>
<td>RMSE (degree)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>under sensor</td>
<td>1.7280</td>
<td>0.8200</td>
<td>0.8090</td>
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<tr>
<td>transient faults</td>
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<tr>
<td>RMSE (degree)</td>
<td>/</td>
<td>0.8320</td>
<td>0.8150</td>
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<tr>
<td>persistent faults</td>
<td></td>
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<tr>
<td>RMSE (degree)</td>
<td>/</td>
<td>1.0130</td>
<td>0.8500</td>
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<tr>
<td>permanent faults</td>
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4. CONCLUSIONS

In this paper, cascaded Kalman filter strategies integrating fuzzy logic have been presented for application in the Springer vehicle. The simulation results are shown in Figs 4 to 13 and compare the system performances based on accuracy, computation efficiency and fault tolerance.

The FLA-FKF has been featured, and its potential for fault detection and recovery has been demonstrated through the simulation. The adaptive information feedback factors improve the robustness of this algorithm.

The FLA-DKF fault tolerance capability is not as good as the FLA-FKF, on the other hand, the FLA-DKF has the advantage of a higher computation efficiency.

The FLA-CKF involves minimal information loss, nevertheless it is not tolerant to sensor faults in an effective way and it has a very high computation load.

For Springer application, the FLA-FKF is considered as the best solution to provide an adaptive and accurate navigation algorithm.

REFERENCES


