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Research Article

Uncertainty Analysis of Integrated Navigation Model for Underwater Vehicle

Zhang Tao, Qi Yong-qi
Department of Mechanical Engineering, North China University of Water Resources and Electric Power, Zhengzhou, 450011, China

Abstract: In this study, to reduce information uncertainty of integrated navigation model for underwater vehicle, we present a multi-sensor information fusion algorithm based on evidence theory. The algorithm reduces attribution by rough set in order to acquire simplified ELMAN neural network and improve basic probability assignment. And then it uses improved D-S evidence to deal with the inaccuracy and fuzzy information, make the final decision. The simulation example shows feasibility and effectiveness of the algorithm.

Keywords: Basic probability assignment, evidence theory, information fusion, uncertainty analysis, underwater vehicle

INTRODUCTION

Significant interest exists in applying underwater vehicles to perform useful missions in the harsh underwater environments. It is one of the primary challenges for navigation and control that acquires accurate position by sensors. The common navigation sensors (Zhao *et al.*, 2010) mainly include: Strapdown Inertial Navigation System (SINS), Doppler Velocity Log (DVL), Magnetic Compass (MCP) and Terrain Aided Navigation (TAN) and so on. The single navigation sensor can't meet the position accuracy of underwater vehicle due to complexity of underwater environments and limitation of single sensor. Underwater navigation research currently focuses on multi-sensor information fusion (Fan *et al.*, 2011). This is done by combining the data from sensors that measure more or less the same thing and estimating the result. Existing fusion algorithm improves the accuracy by kalman filter (Song and Yuan, 2011). From single kalman filter to disperse kalman filter and then federated kalman filter, the premise to improve the navigation accuracy is normal data from sensors and certain measure statistical property (Faa-Jeng *et al.*, 2009). At the environment of strongly interference and large cluster wave, the information from navigation sensors has the feature of incomplete, vague, so that navigation system is hard to get high accuracy from data fusion. Even the same sensor and same accuracy, different environments will lead to different reliability, it is essential for validity and reliability of the system to the reliability of data source.

The D-S data fusion algorithm is presented in order to reduce uncertainty and make decision for reliability of navigation sensor information. The algorithms apply the output of ELMAN network, which is reduced by rough set, to describe the Basic Probability Assignment (BPA) of evidence theory. Then the improved D-S evidences are used to judge the measure information of navigation sensor and increase the accuracy and reliability of integrated system.

In this study, we present a multi-sensor information fusion algorithm based on evidence theory. The algorithm reduces attribution by rough set in order to acquire simplified ELMAN neural network and improve basic probability assignment. And then it uses improved D-S evidence to deal with the inaccuracy and fuzzy information, make the final decision. The simulation example shows feasibility and effectiveness of the algorithm.

INTERGRATED NAVIGATION MODEL OF UNDERWATER VEHICLE

Based on features of underwater navigation information, the system adopts the mixed data of the SINS, DVL, MCP, underwater terrain map and bathometer. In Fig. 1, the structure of the integrated navigation system is shown. The correlation is calculated, which by comparing measured depth $\hat{h}_T$ with the corresponding map depth $\hat{h}_C$ at position $(\hat{L},\hat{\lambda})$ from SINS, to obtain the accuracy position in TAN. Measure vector of longitude and latitude is the difference $(\Delta\hat{L},\Delta\hat{\lambda})$ between the output of TAN and $(\hat{L},\hat{\lambda})$ of SINS. Velocity measure vector is the difference $(\Delta\hat{V}_E,\Delta\hat{V}_N,\Delta\hat{V}_U)$ between the output

Corresponding Author: Zhang Tao, Department of Mechanical Engineering, North China University of Water Resources and Electric Power, Zhengzhou, 450011, China
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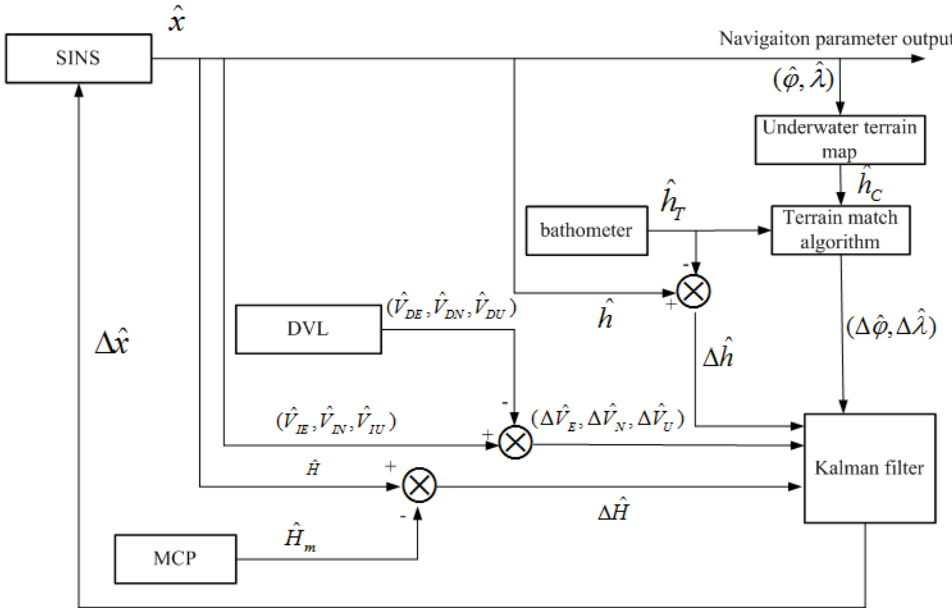

Fig. 1: Principle of integrated navigation system

$(\hat{V}_{DE}, \hat{V}_{DN}, \hat{V}_{DU})$ of DVL and $(\hat{V}_E, \hat{V}_N, \hat{V}_U)$ of SINS. Water depth measure vector is the difference between the output $\hat{h}_T$ of bathometer and $\hat{h}$ of SINS. Heading angle measure vector is the difference between the output $\hat{H}_D$ of MCP and $\hat{H}$ of SINS. The fusion model of integrated navigation system is shown in Zhang (2009).

The kalman filter algorithm of integrated navigation can provides higher navigation accuracy on the premise that each navigation subsystem output normal data. However, only data level integration will lead to incorrect result unless the data offered by navigation subsystem is distort data. The method solved the problem is to judge whether data offered by sensors are credible before information fusion.

NAVIGATION INFORMATION FUSION AND JUDGEMENT BASED ON D-S

D-S evidence theory (Zhang *et al.*, 2008) was originally developed by Dempster, who concerned about the lower and upper probabilities and later Shafer made his contribution by offering belief functions to model uncertain knowledge on the basis of mathematical foundations. D-S evidence theory is an efficient method to process uncertain, incomplete and vague information in data fusion.

Basic concept of D-S evidence theory: A simple set with isolated evidence is treated as a distinguish frame U. Ais a subset of U, m(A)U , describes BPA for A. If $m_1, m_2, \cdots, m_n$ are BPA for $A_1, A_2, \cdots, A_n$ in 2^U, the formula for BPA together with multi-evidence data is set as:

$$m(A) = \frac{\sum_{\cap A_i \subset A} \prod_{i=1}^{n} m_i(A_i)}{1 - \sum_{\cap A_i = \phi} \prod_{i=1}^{n} m_i(A_i)}$$

The step of D-S evidence theory are as followed:

- The credible vector of sensor network node i, j for target Ω can be defined as $Z_i = (p_{i1}, p_{i2}, \ldots, p_{im})$, credible matrix X is converted as $X = Z_i^T * Z_j$
- The sum of main diagonal elements in X is credible factor $\sum_{\cap A_i \subset A} \prod_{i=1}^{n} m_i(A_i)$, respectively the sum of non-diagonal elements constitutes uncertainty factor K by:

$$K = \sum_{\cap A_i = \phi} \prod_{i=1}^{n} m_i(A_i)$$

- Add another sensor network nodes Z_m
- Combination rule of multi-evidence is calculated as:

$$m(A) = \frac{\sum_{\cap A_i \subset A} \prod_{i=1}^{n} m_i(A_i)}{1 - \sum_{\cap A_i = \phi} \prod_{i=1}^{n} m_i(A_i)}$$

Information reduction based on rough set: Evidence data samples are collected as much as possible in order to improve the decision accuracy, however, excessive data will not only take up large storage space and calculate time, but also lower accuracy of decision. In this section, rough set (Li *et al*., 2005) are used to reduce attributes in system frame, delete abundant structure and improve accuracy of decision.

An initial information system can be represented as:

$$S = (U, V, f, A \cup \{d\})$$

where,

- U : The universe, a finite set of N objects $\{x_1 \quad x_2 \quad \cdots \quad x_N\}$
- A : A finite set of attributes
- f : The total decision function such that $f(x,a) \in V_a$ for every $a \in A, x \in U$
- $V = U_{a \in A} V_a$ (where V_a is a domain of the attribute a)

An attribute $a \in A$ is called indispensable in the set A if $POS_{(A-\{a\})}(d) \neq POS_A(d)$. Otherwise the attribute a is dispensable in A . The set of all indispensable attributes in the set A is called the core of A in S and it is denoted by $CORE(A)$. Algorithm calculates $CORE(A)$ by relative domain and computes degree of importance $SIG(a, R, d)$ according to attribute dependence $k_R(d)$. The maximal importance of attribute a_{max} is selected by $k_R(d)$. The algorithm updates Core vector by $CORE(A) = CORE(A) \cup \{a\}$, computes circularly until the result is accurate to the demand and output $CORE(A)$.

Constitute basic probability assignment by ELMAN network: The key of D-S evidence theory is BPA. The common methods such as expert knowledge (Yang and Bai, 2006) and fuzzy decision (Zhang and Chu, 2009) have shortage of certain subjectivity. Therefore, BPA is expressed as the output of ELMAN network due to characteristic of self-study and parallel computing (Nie *et al*., 2010).

Figure 2 shows the structure of a simple ELMAN neural network. ELMAN neural network (Faa-Jeng *et al*., 2009) is a kind of partial recurrent neural network, which consists of two-layer back propagation networks with an additional feedback connection from the output of the hidden layer to its input layer. Compared with common BP neural network, a special context unit is used to record output value before hidden units. The output of context unit at time n is described as:

$$x_{c,l}(n) = \alpha \cdot x_{c,l}(n-1) + x_l(n-1)$$

where,

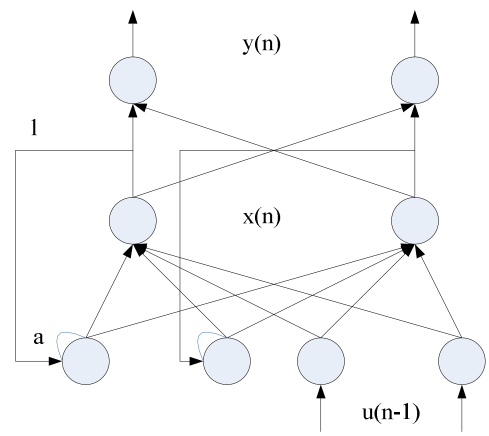

Fig. 2: Structure of ELMAN neural network

- $x_{c,l}(n)$ & $x_l(n)$: The output of context element and hidden layer element
- α : Feedback gain factor

Suppose that there are measure data of N navigation sensors, which be improved by pretreatment and collected m feature vectors. Consider that output of log-sigmoid function is at the interval of (0, 1) it is calculated by ELMAN neural network to achieve n output, which are normalized as BPA of n targets to be identified.

Step of D-S evidence judgment for underwater sensor data: The system integrates the sensor data by federated kalman filter algorithm, including SINS/DVL, SINS/MCP and SINS/TAN. Accuracy of SINS is corrected by Redundancy compensator. When SINS and other navigation modules are integrated, the difference between current output value of SINS and output value of other navigation sensors can be the data source of evidence decision.

The specific step of evidence decision for underwater navigation data fusion is described as follow:

- Primary data are discrete to construct information system $S = (U, V, f, A \cup \{d\})$
- Calculate the degree of dependence by importance of attribute and output $CORE(A)$
- Optimize the structure of ELMAN network by simplified decision table and delete redundant node
- Apply ELMAN neural network to design BPA:

$$m(A_i) = y(A_i) / (\sum_{i=1}^{n} y(A_i) + E_n)$$

where E_n is network sample error

- Judge whether the navigation data is credible. Data is entered into the filter to fuse and calculate if it is credible, on the contrary, the data will be deleted.

SIMULATION AND ANALYSIS

The computational simulation of the integrated navigation system was carried out by Visual C++ 6.0 tools. Gyro's constant error is 5º/h, random noise is 10º/h; acceleration's error is $50\mu g$, random noise is $50\mu g$. The initial latitude is 38º, longitude is 120º and altitude is -100 m, the initial velocity is 5 m/s, the pitch angle and roll angle are 0º, the yaw angle is 45º, the initial latitude error is 0.00254º, longitude error is 0.00446º, altitude error is 10 m, the initial attitude error is 0.15º, the output of DVL and MCP are 0.4 m/s and 0.3º, the error of matching algorithm is 100 m.
In simulation two typical faults is set as:

- Measure data of DVL in 1800, 3600, 5400, 7200 and 10000s are outliers, which increase more than 20% of normal value.
- Simulation time is 5 h, in time of 0-2 and 3-5 h, TAN works in match area, while location correct information is lost caused by flat terrain in time of 2-3 h.

Suppose framework for target identification is {O_1, O_2}, where O_1 represent no fault and O_2 represent fault. According to the front theory, the ELMAN network, which includes 2 input neurons, 9 hidden units and 2 output neurons, is designed to output {O_1, O_2}. The system adopts rough set to reduce attributes of ELMAN network and delete abundant weight connection to improve convergence rate.

Table 1: BPA of sensor

	BPA		
Sensor	O_1	O_2	U
SINS	0.963	0.026	0.011
DVL	0.872	0.104	0.024
MCP	0.825	0.084	0.091
TAN	0.725	0.252	0.023

Table 2: The integrated outcome of $m_{(SINSDVL)}(.)$

	$m_{DVL}(.)$		
$m_{SINS}(.)$	O_1 (0.872)	O_2 (0.104)	U (0.024)
O_1 (0.963)	O_1 (0.839)	ϕ (0.1001)	O_1 (0.023)
O_2 (0.026)	ϕ (0.023)	O_2 (0.003)	O_2 (0.0006)
U (0.011)	O_1 (0.009)	O_2 (0.0011)	U (0.0003)

The algorithm trains the ELMAN network by sensor sample data unless the network error meet demand of threshold, input sensor measure data to ELMAN network and obtains BPA of each sensors, shown in Table 1.

$m_{SINS}(.)$ and $m_{DVL}(.)$ are integrated with D-S evidence to compute BPA of fault target identification for SINS and DVL. The integrated outcome is shown in Table 2.

ϕ is null, inconsistency factor of $m_{SINS}(.)$ and $m_{DVL}(.)$ can be calculated as:

$$K_1 = 0.963 \times 0.104 + 0.026 \times 0.872 = 0.123$$

Following the integration between SINS and DVL, BPA is calculated as:

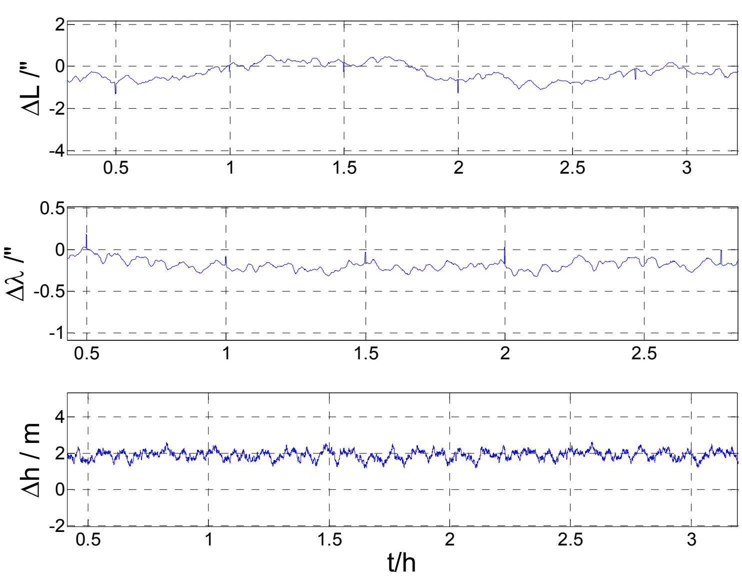

Fig. 3: Location error of filter with evidence algorithm

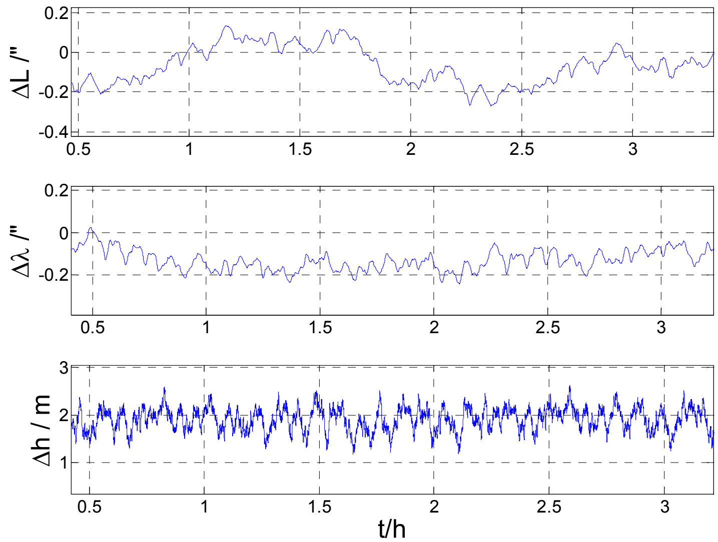

Fig. 4: Location error of filter with improved evidence algorithm

Table 3: Simulation result comparison of navigation parameter

	Error of filter with evidence algorithm		Error of filter with improved evidence algorithm	
Navigation parameter	Mean	Variance	Mean	Variance
Latitude (")	-0.5764	0.5065	-0.0437	0.1880
Longitude (")	-0.3376	0.4176	-0.0183	0.0938
Altitude (m)	1.8662	0.3557	1.5912	0.3420

Table 4: Simulation result comparison of navigation parameter

	Error of filter with evidence algorithm		Error of filter with improved evidence algorithm	
Navigation parameter	Mean	Variance	Mean	Variance
Latitude (")	-0.5764	0.5065	-0.3714	0.3612
Longitude (")	-0.3376	0.4176	-0.2986	0.3367
Altitude (m)	1.8662	0.3557	1.8659	0.3561

$$m_{(SINS\cdot DVL)}\left(O_1\right)=\frac{0.839+0.009+0.023}{1-K_1}=0.993$$

$$m_{(SINS\cdot DVL)}\left(O_2\right)=0.005$$

$$m_{(SINS\cdot DVL)}\left(U\right)=0.001$$

Similarly to SINS/MCP sub-filter and SINS/TAN sub-filter, BPA of fault target identification are computed as:

$$m_{(SINS\cdot MCP)}\left(O_1\right)=0.992\text{ , } m_{(SINS\cdot TAN)}\left(O_1\right)=0.986$$

$$m_{(SINS\cdot MCP)}\left(O_2\right)=0.006\text{ , } m_{(SINS\cdot TAN)}\left(O_2\right)=0.013$$

$$m_{(SINS\cdot MCP)}\left(U\right)=0.001\text{ , } m_{(SINS\cdot TAN)}\left(U\right)=0.001$$

BPA of data uncertainty is reduced to 0.001. Compared with traditional algorithm, sensor fault will be detected accurately by navigation system.

Aiming to the set fault, integrated navigation filter calculation is determined by the evidence algorithm in this study. Under the first fault, the simulation curves of location error with evidence decision algorithm and improved evidence decision algorithm are separately shown on Fig. 3 and 4. Table 3 shows the comparison of location error mean and variance between the two algorithms.

Under the second fault, the simulation curves of location error with evidence decision algorithm and improved evidence decision algorithm are separately shown on Fig. 5 and 6. Table 4 shows the comparison of location error mean and variance between the two algorithms.

From the treatment affection for two typical fault, it is obvious that the system can recognize accurately the sensor fault, which is judged by evidence theory. However, traditional evidence theory utilizes expertise to assign the credibility subjectively. Suppose that the distort data are compensated with synthesis calculation of other normal sensors, then the system makes a erroneous instruction and fuses the fault data so that reduce navigation accuracy. In the study, the novel D-S

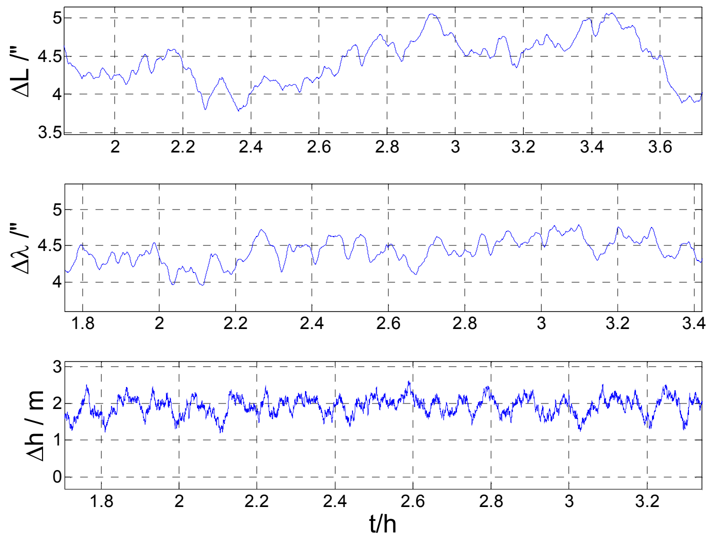

Fig. 5: Location error of filter with evidence algorithm

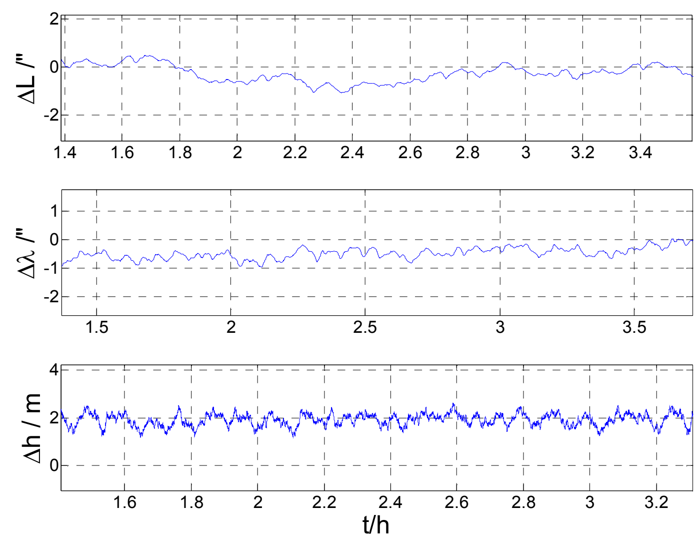

Fig. 6: Location error of filter with improved evidence algorithm

algorithm, which assigns credibility by rough set ELMAN neural network, avoid the interference of the subjective factors, reduce the uncertainty of navigation system.

CONCLUSION

A novel D-S evidence algorithm is presented that makes decision level fusion to reduce the uncertainty of navigation information and improve the accuracy of integrated navigation for underwater vehicles. The algorithm adopts rough set to optimize structure of ELMAN network and eliminate redundant connections. Then ELMAN network is trained with navigation data sample and the output of network, which is BPA of evidence theory, can be contributed to judge the reliability of underwater navigation data fusion. The simulations show that the algorithms improve effectively reliability of navigation system and recognize ability for sensor fault and provide theoretical reference for precision navigation of underwater vehicles.

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