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Review

A hybrid fuzzy method for performance evaluation of fusion algorithms for integrated navigation system

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ARTICLE INFO

Article history:
Received 21 September 2015
Received in revised form 15 November 2016
Accepted 21 June 2017
Available online xxxx

Keywords:
Performance evaluation
Fuzzy AHP
FCE
Integrated navigation

ABSTRACT

Aiming at the problem that traditional evaluation methods based on analytic hierarchy process (AHP) are influenced by subjectivity, this paper proposes an efficacious evaluation method which combines fuzzy logarithmic least square AHP method (fuzzy LLSM) with fuzzy comprehensive evaluation (FCE) method. Fuzzy LLSM is applied to derive the weights and FCE method is for comprehensive evaluation. Then FCE method would provide evaluation results through synthesizing the derived weight vector and membership matrix by a fuzzy operator based upon weighted average. Considering that the membership matrix requires a crisp weight vector to implement synthesis, but the derived weights have the problems of non-uniqueness and fuzziness, so we deduce the constraints to ensure the uniqueness of weights. And defuzzification of fuzzy weights is realized by using the CFCS (Converting Fuzzy numbers into Crisp Scores) method. As a result, the unique and defuzzificated weights are available to synthesis for FCE method directly. Taking the performance evaluation of SINS/Land-based/GPS integrated navigation system for a numerical example, some simulations have been carried out and we draw the conclusion that, the proposed fuzzy LLSM AHP-FCE method is superior to the existing and representative methods when applied to performance evaluation of fusion algorithm for integrated navigation system.

1. Introduction

Performance evaluation is the essential process of developing fusion algorithm for integrated navigation system. Before the fusion algorithm is put into application, the evaluation process can provide a reference for system design and parameters determination. Besides, it provides a verification platform for navigation system, which would save the test cost and shorten the development cycle [1,2]. Therefore, the performance evaluation plays a critical role in system development.

In the past 30 years, domestic and foreign scholars have put forward many methods to evaluate the performance of various systems [3–6]. Among these methods, the fuzzy LLSM method based upon fuzzy mathematics theory has been widely extended by domestic and foreign scholars. Laarhoven P J M V and Pedrycz W [7] first introduced triangular fuzzy numbers to comparison matrix and adopted the LLSM to derive the weight vector from the triangular fuzzy comparison matrix; Younesiis et al. [8] utilized the fuzzy LLSM method to find weights during the FANP process and obtained the weights of the triangular fuzzy comparison matrix. Chang [9] proposed an extent analysis method (EAM) for the fuzzy analytic hierarchy process, introduced the concept of synthetic extent value and calculated the crisp weights by pairwise comparison. Subsequently, F Ahmed et al. [10] expanded the EAM and used centroid defuzzification and mid number defuzzification to rank the final weights calculated from fuzzy comparison matrices. Teng Y et al. [11] first adopted Apriori algorithm to develop association analysis for evaluation object, made recommendation considering the association between objects and other factors.

However, these method has been successfully applied to evaluate the performance of other systems except navigation system [3–6]. Actually, the performance of fusion algorithms for integrated navigation system depends on many mutual factors. The performance evaluation is a multi-grade process, which involves detection, interconnection, correlation, estimation and synthesis of multi-source information. As a result, these characteristics make performance evaluation more vague and difficult to construct the fuzzy comparison matrix by artificial discrimination. However, the fuzzy LLSM method can decompose mutual factors that difficult to distinguish, build the hierarchical structure, promote the formation

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http://dx.doi.org/10.1016/j.ast.2017.06.027
1270-9638/

of evaluation indices, and then derive their weights ultimately. All of these characteristics make the performance evaluation of fusion algorithms for integrated navigation system quantized. Generally, the fuzzy LLSM method can solve the fuzzy and uncertain problems effectively, and it only requires the fuzzy comparison matrix instead of crisp one. Moreover, the method can weaken the subjectivity and determine a weight vector which is more consistent with the reality.

After solving the weight vector, it is still necessary to seek a method for further comprehensive evaluation. The fuzzy comprehensive evaluate (FCE) method is an effective way to address uncertain and fuzzy boundary problems. It specializes in quantizing contributions of related factors comprehensively and using membership functions to decrease the fuzziness [12]. The method has the advantages of strong comprehensive capacity, while it has some problems, that is, the subjectivity of the index weight is strong and the resolution of the evaluation degree is low. Hence, we combine the fuzzy LLSM with FCE method. The former is used to determine the weight vector and the latter is used to evaluate the index model by the membership function. Then the fuzzy operator based upon weighted average is applied to synthesize the weight vector and fuzzy membership matrix [13]. However, the weight vector determined by the fuzzy LLSM is multivalued and expressed as triangular fuzzy numbers. It is not available for the FCE method to synthesize the weights of various indices directly. Aiming at this problem, the paper deduces condition to ensure the uniqueness of weight vectors and uses CSCF to de-fuzzify the weight vector which is the key to realize the proposed method.

2. Index models of performance evaluation for fusion algorithm

The present indices of performance evaluation for fusion algorithm mainly include: accuracy, real-time, stability and reliability. As is known that, the more indices are given, the better evaluation result will be. Hence, we further expand the above evaluation indices to six parts: complexity, accuracy, effective extent, fault tolerance, convergence and robustness. The expanded evaluation models are organized as follows.

2.1. Complexity index

Considering the execution time and the consumed memory of fusion algorithm, we divide the complexity into two parts: time complexity and space complexity. The time complexity describes the real-time performance of fusion algorithm. And it involves impacting factors, such as filtering states, arithmetic type and hardware capability.

Suppose that the filter interval t_d represents the demand of system and t is actual filter interval, where $t_d > t$. The model (1) is achieved as follows:

$$t = f(N_l, N_m, N_a, N_s, N_r)/v_h \tag{1}$$

where $f = \sum_{i=1}^{k} \alpha_i N_i, \alpha_i$ stands for a weighted coefficient, which is determined by the runtime of N_i; N_l is the number of matrix inversion required for filter; N_m and N_a stand for the number of additions and multiplications respectively; N_s denotes the dimension of state vector; N_r is the residual arithmetic operation; v_h stands for the operation speed. Further, the time complexity index can be defined as follows:

$$D_c = t/t_d \tag{2}$$

In addition, the space complexity index is derived based upon the method of on-line testing. That is, by setting several nodes in each function module, we defined the maximum occupancy rate of memory in neighboring nodes as the space complexity index.

2.2. Accuracy index

Accuracy index embodies the accuracy of system model and measurement information, which can be quantified by mean square deviation of the objective parameters. But in fact, the parameter errors and the measurement noises of nonlinear systems are usually large, so that accidental errors can not be neglected. Hence, we introduce the Monte-Carlo method to characterize accuracy index.

The Monte-Carlo simulation is usually performed based upon the least square estimation method. And accuracy index model for objective parameters can be constructed as shown in Eq. (3):

$$\sigma_{\Delta\partial_\xi} = a(s)\sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{M_i}\sum_{j=1}^{M_i}\Delta\partial_{\xi j}^2} \tag{3}$$

where $\Delta\partial_\xi$ is the error of appointed objective parameters; $a(s) = \frac{\sqrt{2}\Gamma(s/2)}{\sqrt{s-1}\Gamma[(s/2)/2]}$; $s = \sum_{i=1}^{N} M_i$; Γ can be determined by referring to the Gamma distribution table. N denotes the simulation times; M_i stands for sampling points of the ith simulation. Further, through normalizing the objective parameters of different order of magnitude, the normalization model of accuracy index is expressed as follows:

$$D_{pre} = \sqrt{\sum\left(1 - \sigma_{\Delta\partial_\xi}/\max(\sigma_{\Delta\partial_\xi})\right)^2} \tag{4}$$

Statistically, it is concluded that the more Monte-Carlo samples are, the better simulation result would be, which will result in the increasing of calculated amount as well.

2.3. Effective extent index

The effective extent index reflects the overall effectiveness of filtering, and it can be quantified by the proportion of filtering error to measurement error.

Let $\mathbf{X}_m$ be the state vector, and we extract k_1 continuous sampling points for calculation by below equations after the starting time of stable filtering k_0. Denoted by $\boldsymbol{\Delta}_m$ and $\hat{\boldsymbol{\Delta}}$ respectively, the measurement error and the filtering error are given separately by:

$$\boldsymbol{\Delta}_m = \sqrt{\frac{1}{k_1}\sum_{k=k_0+1}^{k_0+k_1}\left(\left[\hat{X}(k) - X(k)\right]^T\left[\hat{X}(k) - X(k)\right]\right)} \tag{5}$$

$$\hat{\boldsymbol{\Delta}} = \sqrt{\frac{1}{k_1}\sum_{k=k_0+1}^{k_0+k_1}\left(\left[\hat{X}_m(k) - X(k)\right]^T\left[\hat{X}_m(k) - X(k)\right]\right)} \tag{6}$$

According to customary quantitative convention [12], the effective extent index can be defined as:

$$D_{\text{valid}} = \begin{cases} 0, & \hat{\boldsymbol{\Delta}}/\boldsymbol{\Delta}_m \geq 1 \\ 1 - \hat{\boldsymbol{\Delta}}/\boldsymbol{\Delta}_m, & \hat{\boldsymbol{\Delta}}/\boldsymbol{\Delta}_m < 1 \end{cases} \tag{7}$$

Obviously, D_{valid} meets the constraint $0 < D_{valid} \leq 1$, and as D_{valid} approaches 1, the effective extent tends to increase progressively.

2.4. Fault tolerance index

The fault tolerance index characterizes the flexible ability of system to keep working properly when it is under large disturbance or fault. The fault information is usually reflected in the residual error $\mathbf{D}_k$ [14], and in the normal work situation, $\mathbf{D}_k$ is a

Please cite this article in press as: X. Wang et al., A hybrid fuzzy method for performance evaluation of fusion algorithms for integrated navigation system, Aerosp. Sci. Technol. (2017), http://dx.doi.org/10.1016/j.ast.2017.06.027