UAV sensor fault diagnosis based on rough set and SVM

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A fault diagnosis method based on rough set and support vector machine separation was proposed in order to realize fault identification and timely fault control during UAV autonomous flight.

This paper expounds the concept of rough sets and support vector machine (SVM) and how to carry out the reduction method based on rough set, with unmanned aerial vehicle (UAV) attitude sensor as instance, rough set was used to extract the UAV signs of the fault diagnosis properties of accelerometer and reduce the condition attributes of decision table and then after the reduction of attribute data sets by training support vector machine for fault classification, and then will test set through the training of support vector machine (SVM) for verification.

The results show that the fault identification rate and classification time can be improved to a certain extent.

Key Words : UAV, SVM, Rough set, Fault diagnosis

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are widely used in various fields of national economy, and the flight safety of UAVs has been paid more and more attention. Sensor is the core of measuring UAV attitude information, which provides safe, reliable and comprehensive data information for UAV flight [1]. The safe flight of a drone largely depends on whether the sensors are malfunctioning. However, unmanned aerial vehicles often fly in harsh environments with strong interference and vibration, so the working state of sensors will be interfered to a certain extent [2]. Especially for sensors such as accelerometer and gyroscope used in inertial navigation, the data information transmitted back to the control system by the sensor will fluctuate abnormally. The excessively large fluctuation range will cause false alarm of the fault diagnosis system and provide inaccurate data information to the UAV flight control system [3].

With the progress of computer technology, the development of artificial intelligence and the development of precision instruments, unmanned aerial vehicles (UAVs) contain more and more precision parts, and the system tends to be intelligent and complicated. The fault diagnosis technology, which is dedicated to improving the reliability of UAVs and reducing the failure rate, has emerged. At present, the performance of sensor is of great significance to ensure the normal state of UAV, and sensor fault occupies the largest proportion of UAV fault types. Although the sensor is composed of many precision components, it is easy to face various problems under long-term bad working conditions, but if the sensor fault can be located and control reconstruction in time, the safety and reliability of the whole system can be improved to a certain extent.

Due to the small amount of fault sample data that can be acquired by UAV sensor, it is likely that the fault model of UAV sensor can not be established accurately if the traditional machine learning or expert system method is adopted for fault diagnosis, and the fault can not be located accurately eventually. Support vector machine technology is especially good at dealing with small sample faults with small amount of data. Its biggest advantage is that it can not only avoid "machine overlearning", but also can process nonlinear data efficiently and avoid the dimensional disaster of feature space. The core of rough set technology is to eliminate redundant samples, achieve attribute reduction and value reduction of fault sample data, and reduce data dimension and training complexity of fault sample. Based on rough sets and support vector machine (SVM) technology, give full play to its own technological advantage, will be after rough intensive Jane should have good classification characteristics of the minimalist failure of sample set as the input into the support vector machine (SVM), greatly optimize the time and computing complexity of fault diagnosis, and can significantly improve the uav sensor fault diagnosis accuracy.

2. ATTRIBUTE REDUCTION BASED ON ROUGH SET THEORY

Rough set theory was put forward by Polish scholars in 1982[4]. Rough set theory is a mathematical tool to study inexact and uncertain knowledge.

For A classification problem determined by N attributes, it is constructed into A decision system <U, A, V, f>; Where U={x_1, x_2, x_3... , x_n} is the domain composed of non-empty finite sets,V is the range;

f: U × A → V is an information function, representing the mapping relationship between the sample and its attribute value.

A=C∪D, Where C is the conditional attribute set and D is the categorical decision attribute set; and C∩D= Φ（null set）.

The upper and lower approximations of rough sets are defined as

$$\overline{R}X = \cup\{Y \in U/R : Y \cap X \neq \varnothing\}$$

(1)

$$\underline{R}X = \cup\{Y \in U/R , Y \subseteq X\}$$

(2)

So the boundary region of subset X is zero

$$BN_R(X) = \overline{R}X - \underline{R}X$$

(3)

$$Pos_R(X) = \underline{R}(X)$$

(4)

The positive domain of R called subset X,

$Neg_R(X) = U - \underline{R}(X)$ called the negative domain of R of subset X.

The dependence of decision attribute D on condition attribute B

$$\gamma_B(D) = \frac{|Pos(D)|}{|U|}$$

(5)

For the above decision system <U, A, V, f>, $\forall B \subseteq C \; a \in B$; The importance of condition attribute A to decision attribute D is defined as follows: $SIG(a,B,D)=\gamma_B(D)-\gamma_{B-\{\alpha\}}(D)$.

Reduction of knowledge: given a knowledge base $K=(U,R)$ and a class of equivalence relations $P\subseteq R$ on it, for any $G\subseteq P$, if G satisfies the following conditions:

(1) G is independent, that is, every element of G is indispensable;

(2) Indistinguishable relation $IND(G)=IND(P)$, it does not affect the partition of knowledge base.

G Then G is a reduction of P, so it is called as $G\in \mathrm{Re}d(P)$, $\mathrm{Re}d(P)$ represents the set composed of all reductions of P.

Kernel of knowledge: Given a knowledge base $K=(U,R)$ and a set of equivalence relations $P\subseteq R$ on it, for any $Q\in P$, if Q satisfies

$$IND(P-\{Q\})\neq IND(P) \quad (6)$$

Then Q is called necessary in P, and the set composed of all necessary knowledge in P is the Core of P, denote as Core(P).

Relative reduction of decision system: Given a decision system, if the conditional attribute subset B satisfies the following conditions:

(1) $\gamma_B(D)=\gamma_C(D)$, that is $Pos_B D=Pos_C(D)$, conditional attribute subset B a nd C have the same classification ability;

(2) $\forall a\in B$, $\gamma_B(D)>\gamma_{B-\{a\}}(D)$, there is no redundancy in conditional attribute subset B.

Subset B is a relative reduction of the conditional attribute set C.

3. THEORY OF SUPPORT VECTOR MACHINES

The support vector machine (SVM) theory was proposed by Vapnik in the 1990s and has been successfully applied to classification problems. SVM is a new learning method developed based on Vapnik-Chervonenkis (VC) dimension theory and structural risk minimization principle, and has good generalization performance[5].

The support vector machine method is the optimal classification hyperplane from the linearly separable case. For the two types of classification problems, it is that the training sample set {(xi,yi), I =1,2...,n}, consisting of 2 categories, marked as positive (yi =1), if belonging to class 2, marked as negative (yi =-1). If Yi can be separated without error by a hyperplane, and the distance between the vector closest to the hyperplane and the hyperplane is the greatest, then the hyperplane is called the optimal hyperplane. The heterogeneous vector closest to the hyperplane is called the support vector.

In practical application, many cases are nonlinear classification problems. For nonlinear cases, SVM uses the nonlinear mapping algorithm of kernel feature space to map the training samples to a high-dimensional linear space through the mapping function $\phi(x)$, and then the linear SVM is used for classification or regression estimation in the high-dimensional space, which put $\phi(x)$ into the optimization problem:

$$\min\left[\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_iy_j\alpha_i\alpha_j\left[\phi(x_i)\phi(x_j)\right]+\sum_{i=1}^{n}\alpha_i\right]$$

(7)

$$s.t.\sum_{i=1}^{n}y_i\alpha_i=0,\ 0\leq\alpha_i\leq C$$

In order to avoid the complicated problem of high dimensional calculation, the kernel function is used to reduce the complexity of calculation

$$K(x_ix_j)=\phi(x_i)\phi(x_j)$$

The original optimization problem is converted to

$$\min\left[\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_iy_j\alpha_i\alpha_jK(x_ix_j)+\sum_{i=1}^{n}\alpha_i\right]$$

(8)

$$s.t.\sum_{i=1}^{n} y_i\alpha_i = 0,\ 0 \le \alpha_i \le C$$

In order to avoid the complicated problem of high dimensional calculation, the kernel function is used to reduce the complexity of calculation.And the discriminant function of nonlinear problem is obtained

$f(x) = \mathrm{sgn}\left[\alpha_i y_i K(x_i x_j) + b\right]$ (b is the constant term of the equation of the hyperplane) (9)

In SVM, kernel function satisfying Mercer condition is used to replace mapping function. In this paper, the radial basis kernel function with better application is selected

$$K(x, x_i) = \exp\left(-\|x - x_i\|^2 \Big/ 2\sigma^2 \right) \quad (10)$$

σ>0 is the bandwidth of the Gaussian kernel,and || · || represents vector model.

4. DIAGNOSIS METHOD

The fault diagnosis should not only distinguish the normal state from the abnormal state, but also determine the abnormal state caused by the fault of the sensor. Therefore, the multi-classification support vector machine should be used to solve the multi-class problems. The multi-classification SVM algorithm mainly has two methods[6]: one is to design a SVM between any two types of samples, so k (k-1)/2 SVMs are required to be designed for the samples of K categories. When an unknown sample is classified, the category with the most votes is the category of the unknown sample. The other is to group the samples of a certain category into one category successively during training, and the remaining samples into another category. In this way, k SVMs are constructed from the samples of k categories. In classification, the unknown samples are classified as those with the largest value of the classification function.

When there are many signs of fault samples, th e learning speed of support vector machine will be very slow, and the efficiency of using the original d ata for fault diagnosis is relatively low. Therefore, t his paper adopts rough set theory to reduce the attri butes of samples before fault diagnosis, removing t he redundant attributes from the conditional attribut es, thus simplifying the diagnosis process and impr oving the diagnosis efficiency[7]. The steps of suppo rt vector machine fault diagnosis method based on r ough set proposed in this paper are as follows[8]:

1) Data preprocessing with rough sets. Firstly, the importance degree of each attribute is calculated , and the conditional attribute with low value of imp ortance function is removed. Finally, the attribute k ernel is calculated and the attribute reduction set is determined.

2) Training support vector machines. The samp les processed by rough set are used as the training s et of support vector machine. By choosing appropri ate kernel function type and parameters, other para meters are initialized to train the support vector mac hine.

3) Abnormal diagnosis. For the test set sympto m, we simplified the decision table by using the met hod of attribute reduction of the Rough Set introduc ed in the paper. The conditional attributes with low importance were selected, and a new decision table after reduction was established. Then, the decision t able was input to the trained support vector machin e for normal and abnormal classification, and finall y the diagnosis results were obtained.

5. TYPE OF UAV SENSOR

(1)The failure mode of airborne sensor[9]

At present, sensor failures of UAVs are mainly divided into the following categories:

1)Sensor short circuit fault: it is a common fault with serious consequences. The sensor suddenly fails and the output value becomes zero. The mathematical model is as follows:

the output value $y_{out} = 0$

2)Sensor constant deviation fault: the difference between the sensor output value and the actual value is a fixed constant, Which is usually caused by bias voltage or current. The mathematical model is as follows

$$y_{out} = y_{in} + \Delta_i$$

Δ_i a constant,and y_{in} is the actual value.

3)Sensor open-circuit fault: the fault is manifested as the sensor output exceeding a threshold value (maximum value), and the mathematical model is as follows

$$y_{out} = \varepsilon ,\varepsilon \text{ is a threshold value .}$$

4)Multiplicative sensor fault: this type of fault is generally due to the increase of the multiplier factor after the standard output of the sensor, resulting in a wide range of output data errors. The main reason is that the built-in circuit of the sensor is damaged by external interference.

5)Sensor outlier data fault: this fault often appears on Global Positioning System(GPS) and other sensors. At a certain moment, there will be a large error, but the output after that is correct, which is a temporary fault. The main reason is that GPS star search conditions are bad, communication interference.

(2) Failure samples

The airborne sensor system integrates the three-axis gyroscope, three-axis accelerometer, electronic compass (three-axis sensor), GPS, sonar altimeter, tachometer (Hall element) and other sensors to obtain the attitude, speed, position and other information required by the autonomous flight of the UAV. In the attitude sensor system, the triaxial accelerometer is the most likely sensor to fail due to the difference of device reliability and shock resistance, and the experimental data also show that the triaxial accelerometer has the highest actual failure rate. This paper adopts the fault data of the triaxial accelerometer in the experiment.Table 1 Fault symptom and its corresponding attribute value table, Table 2 Fault type and its corresponding symptom table,1 means no and 0 means yes.[10]

Table 1: Fault symptom and corresponding attribute value table

number	Type of fault symptom	Attribute values
X1	Whether the measured data are far from the mean	X1=0 X1=1
X2	Whether the measured data is greater than a threshold	X2=0 X2=1
X3	Whether the measured data is always 0	X3=0 X3=1
X4	Whether the instruction system is executed as expected	X4=0 X4=1
X5	RAM read and write is correct	X5=0 X5=1
X6	Whether the timer can overflow on time and clear the flag bit	X6=0 X6=1
X7	Ability to communicate information	X7=0 X7=1

Table 2: Fault types and their corresponding symptom tables

Serial number	The fault types	The corresponding sign
D1	trouble-free	All modules are fine
D2	Sensor module failure	X1,X2,X3
D3	CPU module failure	X4
D4	RAM module failure	X5
D5	Timer module failure	X6
D6	Wireless transceiver module failure	X7

6. RESULTS

Using Tables 1 and 2, the decision table of fault samples can be established, as shown in the following table:

Table 3: Fault sample decision table

Samples	Types of property						Decisions
U	X	X	X	X	X	X	X	D

	1	2	3	4	5	6	7	
1	0	0	0	0	0	0	0	D1
2	0	0	0	0	0	0	0	D1
3	1	1	0	0	0	0	0	D2
4	1	0	1	0	0	0	0	D2
5	1	1	0	0	0	0	0	D2
6	1	0	1	0	0	0	0	D2
7	0	0	0	1	0	0	0	D3
8	0	0	0	1	0	0	0	D3
9	0	0	0	1	0	0	0	D3
10	0	0	0	1	0	0	0	D3
11	0	0	0	0	1	0	0	D4
12	0	0	0	0	1	0	0	D4
13	0	0	0	0	0	1	0	D5
14	0	0	0	0	0	1	0	D5
15	0	0	0	0	0	0	1	D6
16	0	0	0	0	0	0	1	D6

Relative Core(P)={X4,X5,X6,X7} can be obtained by the above method of attribute reduction, and the final attribute set T={X1,X4,X5,X6,X7} is a relative reduction, so the decision table 4 after reduction is as follows:

Table 4: Fault sample decision table after reduction

	X1	X4	X5	X6	X7	D
1	0	0	0	0	0	D1
2	0	0	0	0	0	D1
3	1	0	0	0	0	D2
4	1	0	0	0	0	D2
5	1	0	0	0	0	D2
6	1	0	0	0	0	D2
7	0	1	0	0	0	D3
8	0	1	0	0	0	D3
9	0	1	0	0	0	D3
10	0	1	0	0	0	D3
11	0	0	1	0	0	D4
12	0	0	1	0	0	D4
13	0	0	0	1	0	D5
14	0	0	0	1	0	D5
15	0	0	0	0	1	D6
16	0	0	0	0	1	D6

The reduced fault decision table is taken as the SVM training sample, and the SVM is trained. After several training sessions, the radial basis kernel function K (x, x_i) is selected as the SVM training model[11],If there exists a transformation from R^n to space H:

$\Phi : R^n \rightarrow H, \quad x \rightarrow \Phi(x)$ (1)

Such that: $K(x_1, x_2) = (\Phi(x_1) \cdot \Phi(x_2))$, where (·) represents the inner product of the space H, and the function K (x1, x2) is the kernel function of $R^n \times R^n$. X_i is the feature vector of training samples; x is the feature vector of the identification sample;

$$K(x, x_i) = \exp\left(\frac{-\|x - x_i\|^2}{2\sigma^2} \right)$$

Eleven sets of data in the reduced fault decision table were randomly selected as the training set, and the remaining five sets of data were used as the test set for testing.Meanwhile, the same data and samples were used to train and test the rough set without rough set attribute reduction.

In MATLAB R2017b environment, we diagnose the fault sample decision table shown in Table 3 by SVM model and RS-SVM(rough set and SVM) model. Select fifteen groups of data corresponding to that of original fault diagnosis sample $\{m_3,m_4,m_5,m_8\}$ as set of training sample and the other five groups of data as set of testing sample.In order to reduce the impact of computer accidental errors, we conduct 100 times tests, the time-consuming and contrast results of diagnostic accuracy are shown in Table 5.

Table 5: The results

Fault Diagnosis Model	The time of diagnosis (Times / s)	Diagnostic accuracy (η%)
SVM model	0.285	88
RS-SVM model	0.160	95

The time-consuming of using the RS-SVM model, which is combined rough set and SVM, is just 0.160s, diagnostic accuracy rate is up to 95%, the diagnosis efficiency is much higher than just using SVM model, and also improve the accuracy of diagnosis, the fault tolerance is better.

7. CONCLUSION

A sensor fault diagnosis algorithm based on rough set attribute reduction and support vector machine (SVM) is proposed.

Through the verification of the simulation experiment, the fault can be classified and diagnosed accurately, and the fault has a higher classification accuracy, which provides a new way for the intelligent diagnosis technology of the sensor.

In this paper, the identification and diagnosis of UAV sensor faults are only studied, and the sensor faults of UAV actuator and UAV formation are not studied. Therefore, it is an important research direction of UAV fault diagnosis in the future.

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