Application of Dynamic Uncertain Causality Graph in Spacecraft Fault Diagnosis: Prediction

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Abstract

Intelligent diagnosis system are applied to fault diagnosis in spacecraft. Dynamic Uncertain Causality Graph (DUCG) is a new probability graphic model with many advantages. In this paper, DUGG is applied to fault diagnosis in spacecraft from three aspects: introducing conditional functional events into ordinary DUCG to deal with spacecraft multi-conditions; applying DUCG to solve the causal cycle in spacecraft's fault diagnosis knowledge base; and predicting possible faults when telemetry parameter drift to fuzzy areas. Now, DUCG has been tested in 16 typical faults with 100% diagnosis accuracy.

Keywords

Spacecraft, fault diagnosis, probability inference, knowledge representation.

1. Introduction

Fault diagnosis with artificial intelligent technology is classified into four types: case-based, rule-based, model-based, and data learning-based such as Bayesian Network, Neural Network, Support Vector Machine (SVM), etc.

For case- and data-learning based diagnosis, the most difficult problem is that if the fault does not exist, cases and data do not exist, and corresponding methodology is not applicable.

Although IF-THEN based expert system can represent the knowledge of domain experts, it has obvious drawbacks: first, rule-based expert system is not applicable to calculate rule uncertainties while which widely exists in real world; second, as knowledge expands, the overlapping, inconsistency and conflict are becoming more and more obvious, causing significant difficulties in technology for rule management, revision, and operation; third, the illustration of inference is under performance. Although all the rules can be enumerated, when the rules are many, especially for rule combination, enumeration cannot clearly represent the logic relationship of inference.

Now, artificial intelligent community prefer to Probabilistic Graphical Model, represented by Bayesian Network. In 2012, Judea Pearl, the founder of BN, is awarded by Turning Award for his breakthrough in knowledge representation and inference of traditional rule-based expert system and introducing uncertainty and graph into knowledge representation and inference model. However, BNs still face unsolved problems. For example, logic cycle is not allowed in BNs, otherwise no solution will be found. In many complex systems, such as aerospace system, closed control loops and causal logic cycle are inevitable. Furthermore, affected by the operational attitude and ground operation commands, the condition of spacecraft is constantly changing, causing correspondingly change of normal value range and interaction, for which BNs does not have good solutions.

To overcome the above problems, DUCG, a new intelligent diagnosis model, is presented. Conditional linkage events in DUCG can effective deal with the multi-condition of spacecraft; DUCG can effectively solve the causal logic cycle in spacecraft fault diagnosis; furthermore, DUCG can also predict faults with uncertain evidence with continuous variable.

Section 2 introduces the basic concept and inference of DUCG; section 3 discusses the application, including the cases of fault prediction; sections 4 concludes this paper and outlines the future work.

2. Brief Introduction to DUCG

2.1 Knowledge representation of DUCG

For the variables in real world with complex and uncertain causality, DUCG provides an expression with compact variables and relations, applying chaining inference algorithm to realize highly efficient inference. Compared with other diagnosis methodologies, DUCG shows obvious advantages in the interpretation of fault process and results, relying less on parameter accuracy and the information completeness of knowledge base. In usual cases, DUCG's compact representation can describe the operation mechanism of spacecraft.

DUCG consists of a set of variables or events classified as *B*-type, *X*-type, *G*-type, and *D*-type, connected by directed arcs from cause to results. In DUCG, *B*-type represents the basic/root causal variable or event, denoted as B_i or B_{ij} indexed by *i* as variable, *j* as state, and a comma to separate *i* and *j*, for example $B_{2,1}$. In other words, B_i is an event variable, and $B_{i,j}$ is an event that B_i in state *j*.

X-type represents result variable or event, denoted as X_n or X_{nk}, with *n* indexing variable, *k* indexing state, and a comma to separate, for example $X_{2,3.}$ *X*-type can also represent causal variables or events with more than one input and but not output.

G-type represents logic gate variables or events, drawn as G_i or G_{ij} respectively, to present any logic relations in logic expression among input variables, for example $G_{2,1}$=$X_{2,2}$, $G_{2,2}$=$X_{2,1}$+$B_{2,2}X_{2,0}$, and $G_{2,0}$= "remnant state", etc.

D-type represents default causal event variables, drawn as pentagon, denoting the unclear default parent variables of child variable X_n, equaling to adding a background probability distribution for X_n when the explicit cause expression does not exist.

For convenience, V_i or V_{ij}($V \in \{B, X, G, D\}$) denotes the parent variable or event of X_n, the subscript *i* represents variable number, *j* represents the state of variable V_i with comma to separate, where *j* =o is the normal state or otherwise. Odd number denotes low, even number denotes high. The higher the value, the bigger the deviation.

The directed arc in DUCG denotes the weighted functional event $F_{n;i} \equiv (r_{n;i}/r_n) A_{n;i}$ from parent variable V_i to child variable X_n. $A_{n;i}$ is an event matrix with $A_{nk;ij}$ as its functional event, *k* indexing the matrix line and *j* indexing the column also separated by ";". $r_{n;i}$>0 is the causal relationship intensity between V_i and X_n. $r_n \equiv \sum_i r_{n;i}$, $(r_{n;i}/r_n)$ is the weighted coefficient of $A_{n;i}$. The dashed directed arc in DUCG represents conditional functional events, only valid when satisfying the given conditional event $Z_{n;i}$. When $Z_{n;I}$ is met, the dashed directed arc is changed to solid one, otherwise deleted. $Z_{n;i}$ can be any observable events, such as $Z_{n;i}$=$X_{2,1,}$ $Z_{n;i}$=$B_{3,0}X_{2,2}$, etc.,

The lowercase letter in DUCG represents probability of corresponding events, such as $b_{i,j}$ = Pr{$B_{i,j}$}, $x_{n;k}$= Pr{$X_{n;k}$}, $a_{nk;ij}$= Pr{$A_{nk;ij}$}, $f_{nk;ij}$= Pr{$F_{nk;ij}$}=$(r_{n;i}/r_n)a_{nk;ij}$, among which $f_{nk;ij}$ is the contributed value of $V_{i,j}$ to $X_{n;k.}$ satisfying Pr{$X_{n;k}$}=$\sum_{i,j} f_{nk;ij}$ Pr($V_{i,j}$).

2.2 DUCG Probability Inference

As mentioned above, suppose V_i($V \in \{B, X, G\}$) is the parent variable of X_n, then (1) is valid:

$$X_{nk} = \sum_i (r_{n;i} / r_n) \sum_j A_{nk;ij} V_{ij} \tag{1}$$

When V is X-type or G-type, outspread as (1) or the logic expression of G until all the variables or events become $\{B,A\}$ variables or events and r parameter. When more than one X- or B-type events multiple, logic absorption or exclusive operation are needed after multiplying their expressions, making it the sum-of-products expression of $\{B,A\}$ event or variable and r parameter. Then the uppercase letter is changed to lowercase letter (lowercase represents the probability or probability matrix of the event or event matrix) to get the probability of these expressions. For logic absorption and exclusive operation, see [1] and [2] for detail.

Suppose E as the evidence, for example $E=X_{1,1}X_{2,1}$, and H_{kj} denotes a hypothesis event consisted of $\{B, X, A\}$- type events, with k indexing variable combination (for example $H_k=B_1X_2$) and j indexing state combination (for example $H_{kj}=B_{1,1}X_{2,2}$)

DUCG inference is as follows:

1) Simplify

After getting E, by using the simplified rules 1-10 and 16 in [1] and [2], a large and complex DUCG can be simplified into small and simple ones. The aim of simplifying is to delete invalid causal relationship and irrelevant variables. The calculation scale is decrease exponentially with losing no accuracy.

2) Decompose

In simplied DUCG, suppose at the same time the abnormal event in one only B-type variable is true, DUCG can be decomposed as a set of sub-DUCGs, which can be further simplified according to rule 1-10 and 16. If the sub-graph can explain all the abnormal evidences E', it is retained otherwise deleted. The retained sub-graph of B-type event is added into a hypothesis space S_H, with its members denoted as H_{kj}. If only one member exists in the hypothesis space, inference and accurate result are achieved without calculation. Note that Rule 10 is not applicable to simplified sub-DUCGs as many abnormal evidences in industrial systems require explanations.

3) Event outspread

Suppose more than one members exist in S_H, then E and $H_{kj}E$ should be outspreaded according to each sub-graphs. Applying (1) to outspread E_j ($E = \prod_j E_j$), and combine them by logic AND, OR, XOR, NOT, absorption, and exlusive. r type parameter is also calculated. Finally, the outspread expression of E combining $\{B, D, A, r\}$-type events is achieved. In the same way, $H_{kj}E$ can be outspreaded into the expression only containing $\{B, D, A, r\}$-type events. Then, probability is easy to be calculated based on the outspread event expressions.

4) Probability calculation

$\Pr\{E\}$ and $\Pr\{H_{kj}E\}$ in each sub-graph can be calculated by changing the uppercase letters into lowercase letters in the outspread expression of E and $H_{kj}E$. Experts provide $\{b,a,r\}$-type parameters while constructing DUCG knowledge graph. For the sub-graph i, $\zeta_i = \Pr\{E\}$ and $\zeta_i = \zeta_i / \sum_i \zeta$, and the whole simplified DUCG, probability calculation includes state and order, with the equation of state probability as follows:

$$h_{kj}^s \equiv \zeta_i \Pr\{H_{kj} | E\} = \zeta_i \frac{\Pr\{H_{kj}E\}}{\Pr\{E\}} \tag{2}$$

$E = \prod_j E_j$ denotes the join of evidence events, H_{kj} denotes possible hypothesis, and h_{kj}^s the posterior probability of H_{kj}.

Suppose the rank probability of H_{kj} is equated as:

$$h_{kj}^r \equiv \frac{h_{kj}^s}{\sum_{H_{kj}} h_{kj}^s} = \frac{\Pr\{H_{kj}E\}}{\sum_{H_{kj}} \Pr\{H_{kj}E\}} \tag{3}$$

Obviously, $\sum_{H_{kj} \in S_H} h_{kj}^r = 1$. Based on this, we have the rank probability of all the hypothesis events of possible faults. With only one remaining hypothesis event, the fault case can be uniquely diagnosed.

DUCG inference is featured with chaining and self-relying. The probability of each causality chain is decided by itself. Therefore, the parameters beyond causality chain can be omitted and will not affect accuracy. Under the condition of incomplete knowledge representation (some parameters are not given), DUCG still has accurate inference.

3. The Application of DUCG to Fault Diagnosis in Spacecraft: Prediction

In spacecraft, many telemetry data are continuous. For example, the rotation rate of momentum wheel between 1300-1600 pulses/second is in normal state, high with over 1600 pulses/second and low with below 1300 pulses/second. However, this is not strictly applicable in real cases. Complex numerical calculations will occur in the inference process without the discretization of continuous variables. The propagation of probability density parameters is widely applied to lower calculation complexity, but which is limited in many cases. For example, Gaussian distribution and linear conditions must be met. These limitations is caused by complex distribution and parameter calculation. To solve this problem, continuous variables need to be changed into fuzzy discrete variables, and be dealt with like ordinary discrete variables. The treatment of discrete variables in DUCG is introduced in [1].

In spacecraft system, spacecraft can still operate normally when the telemetry parameters are in the fuzzy areas between normal state and abnormal state, while indicating possible faults in the future. Under this condition, DUCG provides a prediction function: to find the root cause of possible faults and predict the development degree of the root cause.

Suppose V_i, $V \in \{ B, X \}$ is a continuous variable (for example the rotation rate of momentum wheel), where E_i denotes the observed evidence of V_i, $E_i=\{V_i=e_i\}$, and e_i denotes the observed specific value of V_i. As shown in Fig.7, V_i is divided into three discrete states: normal (V_{i0}), low (V_{i1}) and high (V_{i2}). $m_{ij}(e_i)$ is the member of V_{ij} indexed by e_i, abbreviated as m_{ij}. In Fig.1, e_i =1200*pps* denotes V_{i1}, e_i =1450*pps* denotes V_{i0}, e_i =1700*pps* denotes V_{i2} and e_i =1550*pps* denotes V_{i0} and V_{i2}.

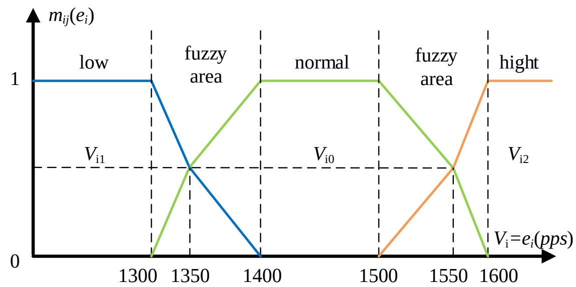

Fig.1 Discretization of continuous variables

Hypothesis 5: $\sum_j m_{ij} = 1$

According to which, m_{ij} is the probability distribution of V_{ij} represented by e_i.

$$m_{ij} \equiv \Pr\{V_{ij} \mid E_i\} = \Pr\{V_{ij} \mid V_i = e_i\}$$

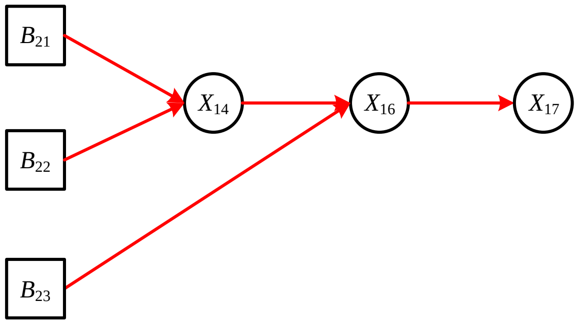

Fig. 2 Illustration 1 of fault prediction

$B_{21,0} \equiv$ {ES output noise is normal}, $B_{21,1} \equiv$ {ES output noise is increased}

$B_{22,0} \equiv$ {ES/earth sensor is normal}, $B_{22,1} \equiv$ {ES/ output noise is disturbed}

$B_{23,0} \equiv$ {friction torque of momentum wheel is normal}, $B_{23,1} \equiv$ { friction torque of momentum wheel is increased}

$X_{14,0} \equiv$ {roll position is normal}, $X_{14,1} \equiv$ {roll position is low}, $X_{14,2} \equiv$ {roll position is high}

$X_{16,0} \equiv$ {rotation rate of momentum wheel is normal}, $X_{16,1} \equiv$ {rotation rate of momentum wheel is low}, $X_{16,2} \equiv$ {rotation rate of momentum wheel is high}

$X_{17,0} \equiv$ {X-axis momentum is normal}, $X_{17,1} \equiv$ {X-axis momentum is low}, $X_{17,2} \equiv$ {X-axis momentum is high}

$$b_{21}=\begin{pmatrix} - \\ 0.05 \end{pmatrix},\ b_{22}=\begin{pmatrix} - \\ 0.01 \end{pmatrix},\ b_{23}=\begin{pmatrix} - \\ 0.05 \end{pmatrix},\ a_{14;21}=\begin{pmatrix} - & - \\ - & 0.25 \\ - & 0.45 \end{pmatrix},\ a_{14;22}=\begin{pmatrix} - & - \\ - & 0.25 \\ - & 0.55 \end{pmatrix},$$

$$a_{16;23}=\begin{pmatrix} - & - \\ - & 0.4 \\ - & 0.5 \end{pmatrix},\ a_{16;14}=\begin{pmatrix} - & - & - \\ - & 0.4 & 0.4 \\ - & 0.5 & 0.5 \end{pmatrix},\ a_{17;16}=\begin{pmatrix} - & - & - \\ - & 0.3 & 0.3 \\ - & 0.4 & 0.4 \end{pmatrix},\ m_{16}=\begin{pmatrix} 0.4 \\ 0.6 \\ 0 \end{pmatrix},\ m_{17}=\begin{pmatrix} 0 \\ 0.3 \\ 0.7 \end{pmatrix}$$

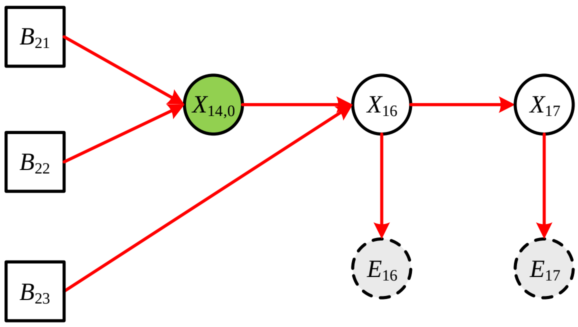

Fig. 3 Illustration 2 of fault prediction

$$\Pr(X_{16,1}) = x_{16,1} = 0.5a_{16,1;14,0}x_{14,0} + 0.5a_{16,1;23}b_{23} = 0.5a_{16,1;14,0}(0.5a_{14,0;21}b_{21} + 0.5a_{14,0;22}b_{22}) + 0.5a_{16,1;23}b_{23}$$

$$= 0.5\times 0\times\begin{pmatrix} 0.5(1 \quad 0.3)\begin{pmatrix} 0.95 \\ 0.05 \end{pmatrix} + \\ 0.5(1 \quad 0.4)\begin{pmatrix} 0.99 \\ 0.01 \end{pmatrix} \end{pmatrix} + 0.5\times(0 \quad 0.4)\begin{pmatrix} 0.95 \\ 0.05 \end{pmatrix}$$

$$= 0.01$$

$$\Pr(X_{16,2}) = x_{16,2} = 0.5a_{16,2;14,0}x_{14,0} + 0.5a_{16,2;23}b_{23} = 0.5a_{16,2;14,0}(0.5a_{14,0;21}b_{21} + 0.5a_{14,0;22}b_{22}) + 0.5a_{16,2;23}b_{23}$$

$$= 0.5\times 0\times\begin{pmatrix} 0.5(1 \quad 0.3)\begin{pmatrix}0.99\\0.01\end{pmatrix} + \\ 0.5(1 \quad 0.2)\begin{pmatrix}0.95\\0.05\end{pmatrix}\end{pmatrix} + 0.5\times(0 \quad 0.5)\begin{pmatrix}0.95\\0.05\end{pmatrix}$$

$$= 0.0125$$

$$\Pr(X_{16,0}) = x_{16,0} = 1 - x_{16,1} - x_{16,2} = 0.9775$$

$$\Pr(X_{17,0}) = x_{17,0} = a_{17,0;16}x_{16} = (1 \quad 0.3 \quad 0.3)\begin{pmatrix}0.9775\\0.01\\0.0125\end{pmatrix} = 0.98425$$

$$\Pr(X_{17,1}) = x_{17,1} = a_{17,1;16}x_{16} = (0 \quad 0.3 \quad 0.3)\begin{pmatrix}0.9775\\0.01\\0.0125\end{pmatrix} = 0.00675$$

$$\Pr(X_{17,2}) = x_{17,2} = a_{17,2;16}x_{16} = (1 \quad 0.4 \quad 0.4)\begin{pmatrix}0.9775\\0.01\\0.0125\end{pmatrix} = 0.009$$

$$a_{16E;16} = (m_{16,0}/a_{16,0} \quad m_{16,1}/a_{16,1} \quad m_{16,2}/a_{16,2}) = (0.4/0.9775 \quad 0.6/0.01 \quad 0/0.0125) = (0.4092 \quad 60 \quad 0)$$

$$a_{17E;17} = (m_{17,0}/a_{17,0} \quad m_{17,1}/a_{17,1} \quad m_{17,2}/a_{17,2}) = (0/0.98425 \quad 0.3/0.00675 \quad 0.7/0.009) = (0 \quad 44.44 \quad 77.78)$$

$$E = E_{16}E_{17} = A_{16E,16}X_{16}A_{17E,17}X_{17} = A_{16E,16}X_{16}A_{17E,17}A_{17,16}X_{16} = A_{16E,16} * A_{17E,17}A_{17,16}X_{16} = A_{16E,16} * A_{17E,17}A_{17,16}A_{16,23}B_{23}$$

$$\Pr(E) = a_{16E,16} * a_{17E,17}a_{17,16}a_{16,23}b_{23} = (0.4092 \quad 60 \quad 0)*(0 \quad 44.44 \quad 77.78)\begin{pmatrix}1 & 0.3 & 0.3\\0 & 0.3 & 0.3\\0 & 0.4 & 0.4\end{pmatrix}\begin{pmatrix}1 & 0.1\\0 & 0.4\\0 & 0.5\end{pmatrix}\begin{pmatrix}0.95\\0.05\end{pmatrix}$$

$$= (0.4092 \quad 60 \quad 0)*(0 \quad 44.44 \quad 77.78)\begin{pmatrix}0.9685\\0.0135\\0.018\end{pmatrix} = (0.4092 \quad 60 \quad 0)*(0 \quad 0.59994 \quad 1.4)$$

$$= 35.9964$$

$$B_{23,1}E = E_{16}E_{17}B_{23,1} = A_{16E;16} * A_{17E;17}A_{17;16}A_{16;23}B_{23}B_{23,1} = A_{16E;16} * A_{17E;17}A_{17;16}A_{16;23,1}B_{23,1}$$

$$\Pr(B_{23,1}E) = a_{16E;16} * a_{17E;17}a_{17;16}a_{16;23,1}b_{23,1} = (0.4092 \quad 60 \quad 0)*(0 \quad 44.44 \quad 77.78)\begin{pmatrix}1 & 0.3 & 0.3\\0 & 0.3 & 0.3\\0 & 0.4 & 0.4\end{pmatrix}\begin{pmatrix}0.1\\0.4\\0.5\end{pmatrix}(0.05)$$

$$= (0.4092 \quad 60 \quad 0)*(0 \quad 44.44 \quad 77.78)\begin{pmatrix}0.0185\\0.0135\\0.018\end{pmatrix}$$

$$= 35.9964$$

$$\Pr\{B_{23,1} \mid E\} = \frac{\Pr\{B_{23,1}E\}}{\Pr\{E\}} = \frac{35.9964}{35.9964} = 1$$

According to the prediction of DUCG: if $\Pr\{H|E\}/\Pr\{H\}>1$, hypothesis H is predicted, or otherwise. In the examples above, $H=B_{23,1}$ is predicted.

4. Conclusion

In this paper, DUCG model is applied to online and real-time fault diagnosis in spacecraft power system. For spacecraft's multi-conditions cases, DUCG knowledge base is constructed including 32 variables, 71 causal relationships, of which 45 are conditional causal relationships (dashed arc). Real-time signal frequency ranges from 100 milliseconds to 16 seconds. The knowledge base includes logic cycle. Based on this knowledge base and applying DUCG's function of prediction, 16 typical faults are tested with 100% accuracy. Besides, possible faults are predicted based on drifting signals. For knowledge base is constructed in a collaborative modular way by multi-people and machines, and automatically synthesized by system itself. It is direct and easy to update and maintain knowledge, convenient for users to understand and operate. By using inference combination, correct inference is applicable even with false signals or incomplete knowledge base, pointing out false signals and knowledge drawbacks.

In future studies, knowledge base construction will be expanded and extended from diagnosis in one spacecraft to synthetic diagnose in more than one spacecraft.

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