Digital Twin Modelling and Data Fusion Validation Study based on D-S Evidence Theory

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Abstract

With the rapid development of information technology and smart manufacturing, digital twin models have been widely used in the simulation and optimisation of production lines. However, the multi-source heterogeneity and uncertainty of production line data bring challenges to the construction and updating of digital twin models. In this thesis, the digital twin model is built, the theoretical values of angles from the PLC control system of industrial robots and the data of actual running angle values collected by sensors are collected for characterisation, and the methods of evidence synthesis and evidence inference in the D-S evidence theory are used for data fusion validation, to determine the input data of the final model, and to improve the accuracy and reliability of the mapping of the digital twin model.

Keywords

Digital Twins; D-S Theory of Evidence; Fusion Verification.

1. Introduction

The core of the digital twin model is modelling and data [1], existing research on digital twin modelling and simulation of production line mainly focuses on the modelling motion simulation of the twin model, the virtual and real mapping with the physical ontology of the production line, and the whole life cycle monitoring and management of the production line. Chenlin Wang [2] used an intelligent algorithm to fuse multi-sensor data to obtain the health status of the robot. Lei Zhenshuo et al. [3] used the fusion of D-S evidence theory and support vector machine (SVM) to study the state assessment method, and the fusion assessment analysis was carried out using D-S evidence theory. However, the reliability verification of the twin model data input in the process of real-time mapping motion simulation has rarely been considered for digital twin models. In this paper, the digital twin modeling of the industrial robot kinematic unit in the intelligent manufacturing production line is used to collect the theoretical value signals of the angles of the joints of the robot body during actual operation (the angle values read from the PLC control system of the robot), and use the sensors to collect the actual value signals of the angles of the joints during operation, so as to determine the probability indexes of the theoretical values of the angles given by the PLC control of the industrial robot and the actual angle values of the joints during the movement. The weight of the probability index of the angle value given by the PLC program control of the industrial robot and the actual angle value of each joint are determined, the affiliation function is constructed, and the final angle evaluation results are obtained through the theoretical verification of the D-S evidence, which are applied to the digital twin model of the industrial robot unit to improve the anti-interference ability of the digital twin model and reduce the decision-making risk of the model.

2. Digital Twin Modelling of Industrial Robot Kinematic Units

2.1 3D Modelling Reduction and Kinematic Joint Definition for Industrial Robot Kinematic Cells

In order to ensure the complete mapping between the twin model and the physical ontology, the physical ontology needs to be modelled. Relying on the model motion control definition function of the digital twin software, according to the motion principle of the physical ontology in the actual operation process, the motion logic of the six motion axes is constructed, and the six motion axes of the robot are redefined, and the coordinate system Joint1-Joint6 that meets the logical relationship of the robot's motion is created in Base and Joint, and at the same time, the robot end-effector is constructed according to the actual requirements, and a closed solution is found for the coordinate system of the six motion joints of the robot, and the logic control tree of the robot model is established. At the same time, the robot end-effector is constructed according to the actual requirements, and the logic control tree of the robot model is established. At the same time, the robot end-effector is constructed according to the actual requirements, and the logic control tree of the robot model is established. At the same time, the robot coordinate system is closed, and the logic control tree of the robot model is established is established, and the subordinate relationship between the motion joints and the axes is clearly defined in the logic control tree, as shown in Fig. 1.



Fig. 1 Definition of Robot Motion Joint Constraint Relationships

2.2 Mapping of Twin Data Acquisition and Transmission for Industrial Robotic Motion Cells

The collection and transmission of twin data is an important basis for the mapping of the digital twin model to the physical ontology. In the data transmission process, the communication between the twin model and the physical ontology is accomplished by using the TCP/IP communication protocol based on the industrial Ethernet architecture, and in the actual operation process, the data transmission is achieved through the socket interface, which ensures the correctness and completeness of the twin data transmission, and improves the rate of the data transmission, and the data transmission framework is shown in Fig. 2.



Fig. 2 Data transfer framework under TCP/IP communication protocols

2.3 Mapping Interaction between Digital Twin Models and Physical Ontologies

This experimental platform can realise the assembly process of the harmonic reducer model. According to the process flow and physical motion process of the target production line, the actual data collected are compared with the simulation of the digital twin model, and the parameters of the twin model are calibrated. The twin model is debugged in combination with the actual running state of the physical ontology to make the twin model fit the ontology better and realise the real-time mapping of the digital twin.

3. Digital Twin Data Fusion Validation Process based on D-S Evidence Theory

D-S evidence theory (Dempster-Shafer) was first proposed by Dempster [4] in the 1960s, Shafer [5] improved this theory. In the process of practical application, Li Qing et al [6] proposed a study of fault diagnosis method based on D-S evidence theory fusing oil and fluid vibration multi-parameters, and Zhang Yuman et al [7] carried out a reasonable assessment of the health state of industrial robots based on D-S evidence theory.

3.1 Establishment of an Identification Framework

Define the basic trust assignment in the recognition framework Θ to be a function under the mapping m: $2^{\Theta} \rightarrow [0,1]$, which satisfies the constraints of:

$$\begin{cases} m(\emptyset) = 0\\ \sum_{A \subseteq \Theta} m(A) = 1 \end{cases}$$
(1)

Where A is a proposition containing one or more hypotheses in the identification framework Θ , and m(A) denotes the degree of confidence that the evidence places in proposition A. Any proposition A that satisfies m(A) > 0 is taken as the evidence factor.

In the actual mapping process of the digital twin model of this experimental platform, three assumptions may occur: Assumption A, the twin model takes the theoretical values of angles given by the PLC control system of the industrial robots as inputs; Assumption B, the twin model takes the angle values collected by the sensors during the actual operation as inputs; Assumption C, the theoretical angle values of the PLC control and the actual angle values of the operation work together as inputs to the twin model . This assumption is used as the identification framework.

3.2 Confidence-building Allocations\

Define the synthesis rule: Assuming that m1 and m2 are mutually independent basic trust assignment functions defined on the identification framework Θ , $A, B, C \subseteq \Theta$, the combinatorial rule for the D-S theory of evidence is as follows.

$$m(A) = \begin{cases} \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1-k}, & A \neq \emptyset \\ 0, & A = \emptyset \end{cases}$$
(2)

Where k is the evidence conflict factor, $k = \sum_{B \cap C = A} m_1(B) m_2(C)$. In the case of 0 < k < 1, the basic probabilities of proposition B and proposition C can be fused using the D-S evidence theory synthesis rule to obtain the final decision.

The values of each joint angle of the industrial robot in this experimental platform based on the planned path in the process of completing the simulated assembly. The trust degree of each proposition in the recognition framework is constructed by combining the trust degree function and likelihood function in D-S evidence theory. Through the analysis, 0 < m(C) < m(A) < m(B) < 1 is taken for better implementation of digital twin mapping.

3.3 Evidence Synthesis Validation

The information provided by multiple evidence is synthetically fused using the D-S evidence theory to synthesise the trust level of each proposition, and the fusion rule is based on equation (2). During the fusion process, the combination of evidence and the updating of the relevant trust degrees are carried out according to the actual needs, and the driving input procedure of the twin model is used for reasoning and decision making.

4. Verification and Analysis of Inference Results

The analysis is carried out on the basis of the trust distribution function during operation, and the results of the reasoning decisions are applied to the industrial robot motion unit.

Based on the trust level after the inference operation, the propositions A, B, and C in the identification framework Θ are solved for the normalisation factor K by taking $m_1(A) = 0.86, m_2(A) = 0.02, m_1(B) = 0.13, m_2(B) = 0.9, m_1(C) = 0.01, m_2(C) = 0.08$, respectively:

$$k = m_1(A)m_2(A) + m_1(B)m_2(B) + m_1(C)m_2(C)$$

= 0.86 × 0.02 + 0.13 × 0.9 + 0.01 × 0.08 = 0.135

Calculations using Dempster's synthesis rules:

$$m_1 \oplus m_2(A) = \frac{\sum_{B \cap C = \{A\}} m_1(B) m_2(C)}{k} = \frac{1}{k} \times m_1(B) m_2(C)$$
$$= \frac{1}{0.135} \times 0.86 \times 0.02 = 0.12740741$$

The same reasoning can be used to calculate:

$$m_1 \oplus m_2(B) = \frac{1}{0.135} \times 0.13 \times 0.9 = 0.866666$$

$$m_1 \oplus m_2(C) = \frac{1}{0.135} \times 0.01 \times 0.08 = 0.00592593$$

According to the results of the fusion verification and the mapping characteristics of the digital twin model of the motion unit of the industrial robot, under the premise of satisfying the trust degree assignment 0 < m(C) < m(A) < m(B) < 1, it is most probable to take the angle value collected by the sensors in the actual running process as the input, at this time, the data of the twin model at a certain moment of time of the extracted sensor's inputs are shown in Table 1.

Axis	Angle/°								
J1 Axis	-72.954	-71.491	-69.938	-68.221	-66.577	-64.951	-63.389	-61.729	-60.210
J2 Axis	-55.432	-56.239	-56.972	-56.761	-58.481	-59.247	-60.040	-60.781	-61.629
J3 Axis	80.789	81.010	81.219	81.401	81.610	81.819	82.008	82.211	82.429
J4 Axis	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J5 Axis	64.832	65.341	65.958	66.512	67.039	67.562	68.211	68.719	69.322
J6 Axis	-9.008	-8.829	-8.609	-8.401	-8.200	-8.028	-7.798	-7.609	-7.401

 Table 1. Real-time acquisition of angle data

The angular data of the six motion axes of the industrial robot motion cell at a particular working moment are selected in the table, and j1-j6 denote the angular values, respectively. It is found through actual testing that the actual simulated motion of the digital twin model is consistent with the actual motion of the physical body, and the simulated motion of the twin model is delayed by about 26ms compared with the physical body. Based on the evidential reasoning of the D-S Evidence Theory, the proposition B: the twin model can satisfy the mapping requirement by taking the angle values collected by the sensors in the actual running process as the input.

5. Conclusion

This study proposes a twin model data fusion verification method based on D-S evidence theory to address the problem that the accuracy and reliability of input data cannot be verified during the real-time mapping of the physical ontology by the data-driven digital twin model. By establishing a digital twin model for the motion unit of an industrial robot in the target production line, the data communication between the twin model and the physical ontology is established to complete the mapping of the twin model to the physical ontology.

In discriminating whether the data inputs of the digital twin model are theoretical values given by the PLC controller or actual values detected by the sensors during the actual operation, D-S evidence theory is fused to solve the problem of discriminating fuzzy evidence. By establishing the confidence assignment for hypothetical propositions in the identification framework, normalised solving and evidence fusion, the final perspective assessment results are obtained, and the hypothetical propositions with the highest confidence are applied to the digital twin model, which improves the reliability of the input data of the twin model, reduces the decision-making risk of the twin model, and provides a reference for better real-time mapping of the twin model.

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