Application of Fault Diagnosis Expert System for Unmanned Vehicle Safety

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Abstract. In order to ensure the safety of the underwater unmanned vehicle (UUV) and reduce the risk of damage or loss during operation, the safety system will be equipped on the UUV. It can accurately locate the fault when the submersible encounters dangerous situations, such as equipment failure and cabin flooding, assess the dangerous situation and make emergency measures, so as to help the underwater unmanned submersible realize self-rescue. Fault diagnosis expert system is a knowledge-based fault diagnosis method, which is suitable for complex systems with incomplete knowledge. However, because the working environment of the underwater unmanned underwater vehicle is very complex and the fault types are diverse and change in real time, the traditional fault diagnosis expert system may not meet the response time requirements of the safety system due to the long response time required. Therefore, the finite state machine technology is applied to the diagnostic expert system to improve the response speed of the diagnostic expert system, and at the same time make the system more flexible and convenient to expand its functions. In addition, the model-based design method was applied to establish the model of the security system in stateflow, and the model verification was carried out. With the help of PLC Coder tool, the code of the target controller was generated and the algorithm was deployed.

Keywords: Safety system, Finite state machine, Remote, repair, troubleshooting, Model-based design

1. Introduction

Because unmanned submersibles face complex and uncertain working conditions when working underwater, sometimes complex underwater tasks are required, so the risk of underwater submarine unloaded or lost during underwater operations is extremely high. Historically, the loss of underwater unmanned submersibles has occurred many times, such as the US “Nereus” HROV, the US “ABE” AUV and the British “Autosub-2” AUV [1]. In order to improve the safety of underwater unmanned submersibles and reduce the chance of loss or damage, an efficient and reliable safety system is essential for underwater unmanned submersibles.

A complete security system consists of two parts: troubleshooting and fault decision making. Fault diagnosis and decision-making methods can be divided into signal processing based methods, model analysis based methods and knowledge based methods [2]. The signal processing based method is a quantitative analysis method that analyses the sensor signals to extract eigenvalues such as amplitude, frequency, and variance to determine the type of fault. Model-based analysis methods also require the use of measurement signals from actual sensors to train fault analysis models. However, the actual
object is usually a nonlinear system that is difficult to model, and the actual data of the sensor cannot be obtained before the actual test, and this is the input condition necessary to design the diagnostic system based on the signal processing method or the model analysis based method. In contrast, knowledge-based methods, such as expert systems, fuzzy inference, and pattern recognition, are less likely to be implemented and more suitable because they do not require an accurate object model [3]. This approach can be used to design fault diagnostic systems for complex systems with incomplete knowledge. The expert system is a computer program system that simulates the human reasoning process of the problem, and then completes the representation of human knowledge, and uses heuristic knowledge instead of exact matching to solve the problem, more accurately reflecting most human knowledge. Typically, diagnostic expert systems are designed in three types: rule-based diagnostic expert systems, model-based diagnostic expert systems, and online diagnostic expert systems. In the rule-based diagnostic expert system, the inference strategy includes forward reasoning (that is, the reasoning process that follows the rules from the original data to the conclusion), backward reasoning (that is, the process of inferring from the target to the data through hypothesis verification), and two-way reasoning.

A new expert system emerged, called the model-based diagnostic expert system. The premise of this method is that the measurement sensor is highly accurate, which is also a key issue for model-based diagnostic expert systems. The online diagnostic expert system is a combination of the knowledge base of the traditional expert system and the interaction process with the target object. Because the online expert system is parallel with the dynamic process, response time becomes a key issue in such expert systems [4]. Aiming at this problem, this paper proposes a method to apply the finite state machine algorithm to the online expert system inference engine to improve the inference performance of the online expert system and apply it to the security system of the unmanned submersible. The finite state machine FSM contains a finite number of system states that can be inferred from the state transition table and complete the state transition after the input event is obtained. It has the ability to describe extremely complex logical reasoning relationships in a clear and concise form, and is ideally suited for the design of complex safety systems for underwater unmanned submersibles.

This paper analyses the working modes of underwater unmanned submersibles, sorts out and lists various fault events that may be encountered by underwater unmanned submersibles, and then completes the classification of fault events and the definition of fault levels. Design the working principle of the safety system, determine the state set of the finite state machine and the input event set according to the fault event classification and fault level definition, and complete the state transition diagram of the finite state machine. Finally, the model of the security system is built in the stateflow model tool to verify the model, and the automatic generation and deployment of the controller code is completed.

2. Safety system design based on finite state machine

The unmanned submersibles in this article can be divided into two modes: remote mode and autonomous mode. In the remote control mode, the water surface operator remotely operates the unmanned submersible to complete the test task; in the autonomous mode, the unmanned submersible self-completes the binding test task. In either of the above modes, the unmanned submersible may work under normal conditions and emergency conditions. Emergency conditions refer to sudden failures or dangers when unmanned submersibles are working underwater. It is necessary to complete decision-making and self-rescue according to unexpected situations, reducing the risk of damage or loss. At this point, the safety system in the underwater unmanned submersible should play the necessary role.

The safety system in this paper consists of the Emergency Controller Unit (EMU), the actuator and the emergency power supply. Among them, the actuator includes a steering system, a submerged floating system, a high pressure blowing system and a throwing system. The finite state machine based fault diagnosis online expert system proposed in this paper runs in the emergency controller
(programmable logic controller PLC).

In practical applications, some fault diagnosis expert systems complete diagnosis and decision making according to the order of fault events, which takes a lot of time [5]. An expert system based on binary decision graph and fault tree classification is an effective fault diagnosis expert system that can guide fault analysis, locate faults and determine emergency strategies [6]. However, the underwater unmanned submersibles in this article may have many concurrent fault events during operation, and even the fault level may change with time. For such dynamic systems, binary decision graphs and fault tree classification methods show their deficiencies in time-varying systems. In order to solve this problem, this paper proposes an improved online fault diagnosis expert system (ODES), which can be used in such complex systems with multiple fault concurrency or fault levels changing with time, and has high flexibility and response speed. Fast, convenient function expansion and so on.

As shown from that, the ODES in this paper has two types of inputs: real-time fault or alarm signals generated by the unmanned submersible master system; and emergency response monitoring signals generated by the emergency controller[7]. They are all stored in the fault database as input to the expert system. The meta-knowledge base and the expert decision rule base constitute the knowledge base of the expert system in the security system.

In the knowledge base of the expert system, the fault event that causes the underwater unmanned submersible to lose working capacity is defined as the top fault category T; the middle fault category A is subdivided into: power and propulsion system fault (A1), hydraulic steering system Fault (A2), submerged and high pressure air system fault (A3), equalization and drain system fault (A4), communication system fault (A5), submersible attitude abnormality (A6), shafting fault (A7). Finally, we can analyse nearly 240 basic fault events X, which correspond to various fault events that may occur in the actual system. Based on past experience and knowledge, the above basic fault events and their combinations can be divided into four levels, including: preventive layer fault events, Class A fault events, Class B fault events, and Class C fault events. The faults corresponding to the four levels are shown in Table 1. When a preventive layer failure occurs, the safety system does not need to be operated, and the master control system on the submersible has the ability to solve the problem by itself. When a Class A, Class B or Class C fault occurs, the emergency controller will take different emergency measures according to the current situation to disengage the submersible.

The inference engine of the online diagnostic expert system in this paper is based on NDFSM design. According to the working mode of the underwater unmanned submersible in this paper, the state collection and input event collection are as follows: 1) State collection: Normal: Normal state; Test: Self In-process; Class A fault status: There is a Class A alarm for steering up and down; Class B fault status: There is a Class B alarm for short circuit blowout; Class C fault status: There is a Class C alarm for dumping; After troubleshooting, it is in standby mode. 2) Input event set: Class A fault alarm: fault1; Class B fault alarm: fault2; Class C fault alarm: fault3; Self-rescue completion; Reset operation; Emergency simulation test starts; Alarm or emergency simulation test ends. Thus, we get the schematic diagram of NDFSM in the security system inference engine.

3. Security system model and code deployment
The model-based design approach is an advanced system development method that frees developers from programming. The use of a graphical design approach makes the goal of development clear, clear and unique, as well as easy to communicate and maintain [8]. The core of the model-based design approach is to model and validate the target object and algorithm, followed by data management and parameter configuration to ensure efficient, high-quality, high-availability code generation, and finally to verify the equivalence. Stateflow is a control logic model tool that models the target system through flowcharts in state machines and simulation models [9]. It is a graphical model tool that has unparalleled advantages in model the logic of complex systems and provides great model convenience for the online diagnostic expert system based on finite state machines. In addition, it provides a simulation environment for model validation and finally generates code for the target controller without requiring developers to manually write code to implement the algorithm functionality. The
model of the security system inference engine is built in stateflow and packaged. The left side of the model is the input signal, and the right side is the output signal, which is the decision result.

PLC Coder is a PLC-oriented code generation tool in Simulink [10]. By setting the IDE to Siemens Step 7, you can automatically generate SCL source files. If the program source file is imported into the portal software, the corresponding PLC program block can be generated [11]. The input and output of this block is consistent with the input and output of the module packaged in stateflow.

4. Security system function verification

The safety system is a double closed loop system. Closed loop 1 is the response loop of the safety system to the real-time fault or alarm signal generated by the master control system; Closed loop 2 is the loop of the response of the safety system to the emergency response [12] after taking emergency measures. If the emergency measures obtained through the closed-loop 1 decision are valid, the closed loop 2 will not determine the emergency measures. Otherwise, the closed loop 2 will upgrade the emergency fault level and take further emergency measures to ensure the safety of the unmanned submersible.

In order to verify the function of the safety system developed by applying the model-based design method, the following emergency process is simulated and verified, and the function is judged according to the result of the security system decision.

4.1. Emergency process of single failure

The emergency process of single failure refers to the single failure of the unmanned submersible. The safety system determines the fault level according to the fault event and takes corresponding emergency measures. Taking the case of a type I fault as an example, the expected response process of the safety system is as follows: fault1 → class A fault event → class A fault state → steering up and down → fault release input the same fault event into the designed safety system, system response. The situation. When t = 1 526 s, the unmanned submersible has a type I fault, and the state of the FSM changes from "normal" to "class A fault state". At the same time, the safety system sends the corresponding emergency rudder angle to the underlying motion controller, which indicates that the safety system has taken corrective measures for the input fault.

4.2. The evolution of the fault level

The evolution of the fault level refers to the emergency process in which the unmanned submersible has a fault event and takes corresponding measures. The unmanned submersible encounters another more dangerous fault event. Taking the type II fault after the occurrence of a type I fault as an example, the expected response process of the safety system is as follows: fault1 → class A fault event → class A fault state → steering up and down → fault2 → class B fault event → class B fault state → short circuit blowing out the same fault event into the designed safety system, the system response is shown. The response of the safety system indicates that the system can correctly switch between different fault levels and take corresponding emergency measures.

4.3. Emergency failure process

The emergency failure process refers to the safety system. After the emergency measures are taken, the unmanned submersibles are not out of danger or show no tendency to escape from danger. At this point, the safety system will take further safety measures, such as replacing the rudder with ballast. The expected response process of the safety system is as follows: Fault1 → Class A fault event → Class A fault state → Steering Upward → Upward failing → Class B fault event → Class B fault condition → Short circuit blowout Enter the same fault event into the safety system. The response of the safety system indicates that the system can correctly identify emergency failure conditions and take further emergency measures.

The simulation results of the emergency failure process show that the security system developed by the model-based design method accurately combines the expert knowledge [13]. Under the various
decision situations that the security system may encounter, it shows the correctness of the decision and proves that it has the ability to provide effective protection for safe operation of unmanned submersibles.

5. Conclusion
In this paper, the finite state machine technology is used to improve the traditional online diagnostic expert system. The model-based design method is applied to facilitate the efficient generation and deployment of controller code, which is faster, clearer and more accurate. A more reliable design method completes the design of the underwater unmanned submersible safety system. The safety system has been verified by a variety of typical decision-making situations, indicating that it has the ability to accurately locate faults and make quick fault decisions. It can provide real-time, effective and reliable basic safety for underwater unmanned submersible operations. At present, the security system is biased towards decision-making and logic control. However, underwater unmanned submersibles may also face more complicated situations. For example, in the process of self-rescue, it is also necessary to consider the avoidance of obstacles and the control of safety posture. In this case, the safety system needs to have the motion control function when the actuator fails, and these have not been considered in the design of the safety system. Therefore, integrated decision-making, logic control, sensor information acquisition and processing, and closed-loop motion control, to develop a more comprehensive and intelligent security system for underwater unmanned submersibles will be the main research content in the future.

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References
[1] Liu X, Sheng Z, Yin C, et al. Performance analysis of Routing Protocol for Low power and Lossy Networks( RPL) in large scale networks. IEEE Internet of Things Journal, vol. 4, no. 6, pp. 2172-2185, 2017.
[2] Ancillotti E, Bruno R, Conti M. The role of the RPL routing protocol for smart grid communications. IEEE Communications Magazine, vol. 51, no.1, pp. 75-83, 2013.
[3] Gungor V C, Hancke G P. Industrial wireless sensor networks: Challenges, design principles, and technical approaches. IEEE Transactions on industrial electronics, vol. 56, no. 10, pp. 4258-4265, 2009.
[4] Ghaleb B, Ai-Dubai A, Romdhia I, et al. Drizzle: Adaptive and fair route maintenance algorithm for Low-power and Lossy Networks in IoT. Proceedings of the International Conference on Communications ( ICC) , pp. 1-6, 2017.
[5] Winter T, Thubert P, Brandt A, et al. RPL: IPv6 routing protocol for low-power and lossy networks: RFC 6550. Internet Engineering Task Force( IETF) , pp. 1-157, 2012.
[6] Awad A M A, Ab Rahim R, Hashim A H A. Queue backlog as a node metric for RPL protocol. Proceedings of the International Conference on Computer and Communication Engineering( ICCCE) , pp. 246-250, 2016.
[7] Kim H S, Kim H, Paek J, et al. Load balancing under heavy traffic in RPL routing protocol for low power and lossy networks. IEEE Transactions on Mobile Computing, vol. 16, no. 4, pp. 964-979, 2017.
[8] Levis P, Clausen T H. The Trickle algorithm: RFC 6206. Internet Engineering Task Force( IETF), pp.1-13, 2011.
[9] Yao Y K, Liu J B, Ren Z, et al. High-efficient centralized network congestion control for RPL routing protocol. Systems Engineering and Electronics, vol. 39, no. 12, pp. 2810-2816, 2017.
[10] Deveza T, Martins J F. PLC control and Matlab/Simulink simulations: a translation approach.
IEEE Conference on Emerging Technologies & Factory Automation, 2009.

[11] Ha S H. PLC Intelligent Transportation Signal Control Based on Algorithm of Function Block Conversion to Instruction List. International Conference on Intelligent Transportation, 2018.

[12] Iova O, Theoleyre F, Nol T. Exploiting multiple parents in RPL to improve both the network lifetime and its stability. Proceedings of the International Conference on Communications (ICC) , pp. 610-616, 2015.

[13] Mielbæe M, Duquennoy S, Quoitin B, et al. Load-balanced data collection through opportunistic routing. 2015 International Conference on Distributed Computing in Sensor Systems IEEE, 2015.