Diagnosis of Complex Failures in Robotic Assembly Systems using Virtual Factories

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Abstract

Robotic assembly systems are widely used in industry to improve the production task. However when they halt their operation due to a failure, it usually takes considerable time to diagnose the system. In this paper, we discuss the results of an approach which uses Virtual Factories to reduce the time spent on diagnosis. The approach proposes building a virtual model of the system and simulating the process many times to identify the possible failure scenarios, their symptoms and likelihood of occurrence before they happen. Then, a diagnosis system can be built based on these results and integrated to the assembly system; and when actual failure happens, the system can come up with the most possible failure scenario using Bayesian Reasoning. A case study and its results are discussed. It is expected that this approach will reduce the downtime because of diagnosis and improve the productivity of large-scale production systems.

Introduction

Robotic manufacturing and assembly systems are widely used in several industries such as automotive, aerospace and consumer electronics. These systems are composed of many automated parts, industry type robots and sensors to complete the production task accurately. However since these systems are composed of many components, they are very complex to deal with when unexpected situations arise. For example, an undetected error may propagate and end up as a detectable failure which may cause the whole line to stop its operation. In this case, it may take considerable time to diagnose the system and identify the main reason(s) for the failure. Several systems [1, 2] are discussed in the literature which use different types of modeling methods, expert systems and fuzzy logic in the diagnosing stage. However since it is impossible to predict all types of failures and likelihood of their occurrence, the usage of these approaches is limited.

In our early works [3, 4], we have discussed a method which uses Virtual Factories to model the robotic system and simulate it to identify failure types and their likelihood of occurrence. In this paper, we present a case study and discuss the results of our method to diagnose complex failures.

Proposed Approach

Our approach is composed of four steps to build a probabilistic diagnosis system:

1. Model the system using a 3D Virtual Factory package.
2. Simulate the process many times using Monte Carlo Simulation.
3. Identify failures, their symptoms and likelihood of occurrence.
4. Build a Bayesian Reasoning based diagnosis system using these results.

Since we use Monte Carlo simulation, the complete sequence of the events that caused a failure and the likelihood of each event are readily available. When an actual failure happens, the reasoning engine processes each possibility of failure from the simulation and come up with most probable one (or multiple) failure classifications. The belief value of each type of failure is calculated by using Bayesian Reasoning with the following formula:

$$Bel(F_k) = \frac{P(Y_o \setminus F_k) * P(F_k)}{\sum_{\forall l} P(Y_o \setminus F_l) * P(F_l)} \quad (1)$$

In the above formula, Y_o indicates the symptoms from the sensor array. F_k is the type of failure from a defined failure array. The formula indicates that the *belief value* for a failure is the ratio of this failure with the given symptoms to the sum of all other possible failures, which can occur under the same conditions.

Sample Case Study

Figure 1 shows the model of a three-robot assembly system. The assembly process is as follows: At first, Rob-A picks up the cylindrical piece from the conveyor and inserts it into the hole of the second piece at the second station. Then, the welding robot (Rob-B) approaches the assembled two pieces and welds these two pieces together. After that, Rob-C picks up the welded piece and places it on the fixture and all of the parts are welded together by Rob-B.

Finally, the complete assembly is transferred on to the conveyor by Rob-C. During the assembly operation, two inspection cameras are used for the verification process. These cameras are placed over the first station where Rob-A picks up the cylindrical piece, and over the fixture respectively.

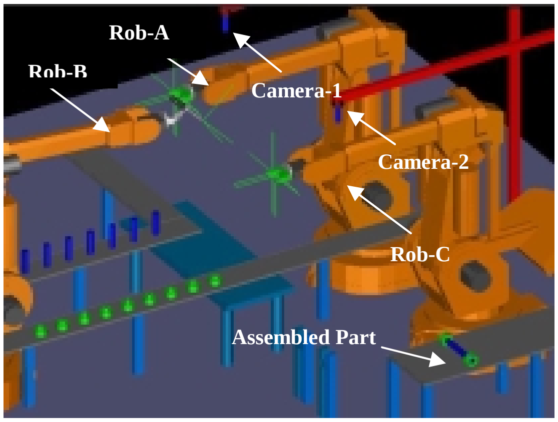

Figure 1: Modeled Assembly System

The operation of this system was simulated using Monte Carlo simulation method by using the properties such as reliability of the sensors, grippers, cameras and robot repeatability. Possible failures, their symptoms and likelihood were recorded. A diagnosis system was built. A threshold value was defined for asking human help where the belief value was not high enough. This value was taken as 0.8.

In order to test the efficiency of the diagnosis system, we assumed that a jamming error was reported at station-1 by the torque/force sensor of Rob-A. The actual reason for this failure is that Rob-A did not release the piece in its gripper and Camera-1 and Rob-A's gripper sensor were malfunctioning to detect this initial error. Furthermore, this error has been propagated and coupled with the Camera-2 failure to detect the incomplete assembly. When the next cycle starts, the next workpiece collided with the previous part still held in Rob-A's gripper. The described failure situation is given in Fig.2.

Information from the sensor array was diagnosed by the system as shown in Table.1. The diagnosed failure reason and its belief value are as follows:

TABLE 1
OUTPUT OF DIAGNOSIS SYSTEM

Diagnosed Failure:	
Belief Value	0.984
Grasping Failure	Rob-A Gripper release failure
Sensor Failures:	Cam.1, Rob-A Gripper, Cam.2

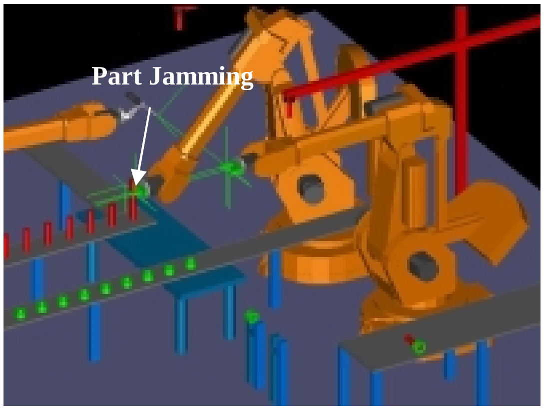

Figure 2: Part Jam

As it can be seen from the outputs, the system was able to identify the real reason of the detected error with a belief value of 0.984. If this value was below the threshold value 0.8, the system would ask help of human maintenance to input more information about the failure. For example, the maintenance person could check several sensors and identify the working components. Then, the system could work on the updated information to identify a failure reason with a higher belief value.

This case study demonstrates that the usage of Virtual Factories would be helpful to build diagnostic systems since it is impossible to anticipate or simulate all failures using actual systems. Automated assembly and manufacturing systems usually stop their operation and the time spent on diagnosis is very crucial for the economic reasons. We believe that using a method described above, the time spent on diagnosis can be reduced dramatically.

References:

1. T. C. Cao, A.C., Sanderson, 1992, *"Sensor-based error recovery for robotic task sequences using fuzzy petri-nets"*, Proceedings of the 1992 IEEE International Conference on Robotics and Automation, Vol.2, pp.1063-1069.
2. Q. Jing , W. Xisen, P. Zhihua, X. Youngcheng, 1996, *"A Research on Fault Diagnostic Expert System Based on Fuzzy Petri Nets for FMS Machining Cell"*, Proceedings of IEEE International Conference on Industrial Technology, pp. 122-125.
3. Baydar C., Saitou K., 2001, *"Off-Line Error Prediction, Diagnosis and Recovery using Virtual Assembly Systems"* Proceedings of the 2001 IEEE International Conference on Robotics and Automation, Seoul, Korea, May 21-26, p. 818 – 823
4. Baydar C., Saitou K., 2001, *"Prediction and Diagnosis of Propagated Errors in Assembly Systems using Virtual Factories"* Application Brief, ASME Journal of Computers and Information Science in Engineering, v. 1:3, p. 261 -- 265.