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THE DESIGN OF BAYESIAN DIAGNOSTIC EXPERT SYSTEM QUERIX AND IT'S ENGINEERING APPLICATION

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Abstract: *Advanced diagnostics of various industrial machines have garnered attention from researchers in recent years as the popularity of smart factories of Industry 4.0 grows. Alongside modern RPA (Robotic Process Automation) systems, which bring various AI methods into the administration of industrial processes, advanced diagnostic and maintenance systems are a logical complement for the digital era of smart factories. This paper focuses on the introduction of a developed expert system used to help diagnose mobile robotic platforms during daily use.*

Keywords: Expert System, Decision Making, Advanced Diagnostic, Autonomous Navigation, RPA.

1. Introduction

Expert systems have gained attention over the last two decades as they bring the possibility of using expert knowledge in various control systems. However, it has lost attraction in favor of artificial neural networks in recent years, which is mostly influenced by the availability of data to train neural network models and the availability of various frameworks to achieve fast time-to-market applications for given solutions.

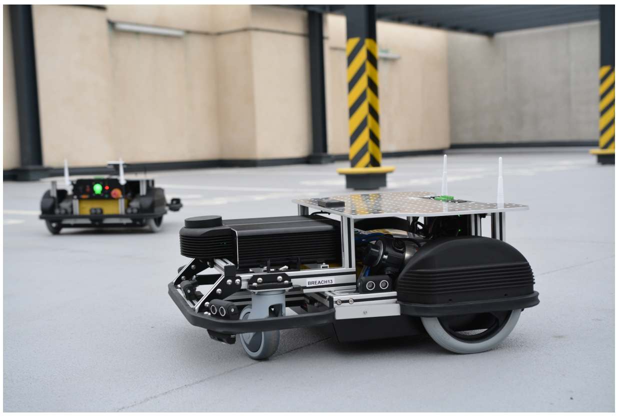

Fig. 1: BREACH mobile robotic platforms in industrial environment (left) and with ZALEELA addon for watering plants in indoor office environment (right).

Even though the popularity and availability of neural network tool-chains create an impression of invincibility(Zhang (2019); Bloecher and Alt (2021); Valerio de Moraes et al. (2022)), this creates a space for

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other AI methods, such as expert systems, and brings the possibility of explaining their decisions(Korb and Nicholson (2004); Thrun et al. (2005)), as it is naturally implemented inside the system itself.

The primary motivation for our work is the direct demand from industry needs where the hi-tech robotic platform BREACH (see figure 1) is used (Krejsa and Vechet (2018); Vechet (2011)). The need for customer service was the motivation to develop an advanced diagnostic assistant which helps unskilled maintenance workers to solve banal problems that otherwise lead to expensive shutdowns and professional services.

2. Materials and methods

To realize real-world experiments, our laboratories are equipped with various autonomous mobile robots that share some construction elements. The main robot is called BREACH (see figure 1 left), an industrial platform used for the development of customer-based industrial applications. This platform was developed in cooperation with Bender Robotics company and is widely used in mobile robotics application tasks. The BREACH platform was used for the realization of a student project called ZALEELA (see figure 1 right), which main task was to water plants in an indoor environment. The third platform is a mobile robot LEELA (see figure 2), which is a light version of the BREACH platform. The LEELA robot was also used in smart factory laboratories at National Cheng-Kung University (NCKU) as it is our partner workplace.

Fig. 2: LEELA mobile robotic platforms in indoor office environment

Above mentioned mobile robots are build up using standard set of equipment as laser range finders (Hokuyo Lidars), ultrasonic distance sensors SRFxx, encoders, motor controllers (RoboClaw) with control software based on Robot Operating System (ROS see Vechet et al. (2020)).

3. Expert system shell

The main task of our expert system called Querix was to support high-level maintenance decisions, whether a potentially occurring problem has a local immediate solution or external professional service is needed.

For such purpose, a set of possible hypotheses was defined together with a set of evidence that can be observed by maintenance workers, and the result of the expert system is advice on how to solve potential problems (see table 1). The Bayesian network was used to model such behavior (see Murphy (2001); Murphy et al. (2001); McGuffin (2012); Vechet et al. (2016)).

Using variables defined in table 1, the inference rules are prepared. They could be for better understanding described by natural language or by IF-THEN rules. See table 2 for a few sample rules which are used for decision making.

To calculate the probability that the Lidar is being not connected properly using the information about internal visualization process RViz running together with mapping module and information gathered from Lidar is demonstrated using equation 1.

$$P(lidarConnected|rViz, mapVisible, lidarInMap) = \eta P(rViz|lidarConnected) \\ P(mapVisible|lidarConnected)P(lidarInMap|lidarConnected)P(lidarConnected) \quad (1)$$

Tab. 1: Limited set of variables used in knowledge base to create the bayesian network which represents the model of the system

Cause/Hypothesis		Effect/Evidence		Action	
ID	Description	ID	Description	ID	Description
CA	Encoder not connected	EA	RViz running	AA	Check cable
CB	RoboClaw not connected	EB	Map of environment is visible	AB	Check battery
CC	SRFxx not connected	EC	Lidar data visible in the map	AC	Service needed
CD	Lidar not connected	ED	Robot is well localized	-	-
CE	Battery low	EE	Robots goal properly defined	-	-
CF	Problem with RoboClaw	EF	Robot is moving	-	-
CG	Robot doesn't start properly	-	-	-	-

Tab. 2: Samples of applied rules and adequate conditional probabilities

Description	IF RViz AND Map running AND not Lidar THAN the Lidar is not connected
Rule	if EA and EB and not(EC) then CD
Probability	$P(lidarConnected \vert rViz, mapVisible, lidarInMap)$
Description	IF RViz AND Localization AND Goal defined AND robot no move THAN Check accu
Rule	if EA and ED and EE and not(EF) then CE
Probability	$P(batteryLow \vert rViz, localized, goalSet, robotNotMoving)$

$$P\left(rViz = T|lidarConnected = F\right) = 0.3 \tag{2}$$
$$P\left(mapVisible = T|lidarConnected = F\right) = 0.2 \tag{3}$$
$$P\left(lidarInMap = F|lidarConnected = F\right) = 0.99 \tag{4}$$
$$P\left(lidarConnected = F\right) = 0.5 \tag{5}$$

$$P\left(rViz = T|lidarConnected = T\right) = 0.9 \tag{6}$$
$$P\left(mapVisible = T|lidarConnected = T\right) = 0.95 \tag{7}$$
$$P\left(lidarInMap = F|lidarConnected = T\right) = 0.01 \tag{8}$$
$$P\left(lidarConnected = T\right) = 0.5 \tag{9}$$

$$P\left(lidarConnected = F|rViz = T, mapVisible = T, lidarInMap = F\right) = 0.0297 \tag{10}$$
$$P\left(lidarConnected = T|rViz = T, mapVisible = T, lidarInMap = F\right) = 0.004275 \tag{11}$$

$$Bel\left(lidarConnected = F\right) = \frac{0.0297}{0.027 + 0.004275} = 0.874 \tag{12}$$
$$Bel\left(lidarConnected = T\right) = \frac{0.004275}{0.027 + 0.004275} = 0.126 \tag{13}$$

To calculate the belief (see eq. 12) that the Lidar is (not) properly connected, we use the Bayesian conditional probability with a classic approach to use a total probability law to calculate the parameter η (eq. 1) as a normalization constant and apply it to all joint probabilities 10. The input probabilities used in the sample calculations are defined in equations 6 and 2.

The resulting belief is nearly 90% in favor that the Lidar connection is broken, which, even in this simple case, can serve as guidance for untrained maintenance to solve the issue immediately.

4. Conclusions

The briefly presented core of the expert system Querix represents a way to address the problem of advanced diagnostics of industrial machinery within the environment of smart factories of Industry 4.0.

We have developed an inference engine suitable for online monitoring of given machines, serving as non-stop working maintenance to help solve sudden failures or warn in advance.

As the system is successfully used together with autonomous mobile robots in smart factories, future work is focused more on searching for suitable industrial applications where the expert system can be applied, tested, and developed into a more complex diagnostic system for smart factories.

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