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AI BASED ASSISTIVE MAINTENANCE OF MACHINES VIA QUERIX EXPERT-SYSTEM

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Abstract: *In the context of the expanding domain of Industry 4.0 and the integration of smart factories, there has been increasing interest in advanced diagnostics for industrial machines. This paper introduces an evolution of state-of-the-art expert system designed to aid in diagnosing issues encountered during the operation of industrial machines. Advanced diagnostic and maintenance systems serve as crucial components in the digital era of smart factories, so as the use-case scenario a mobile robotic platforms was used.*

Keywords: Assistive maintenance, decision making, advanced diagnostic.

1. Introduction

Expert systems have been a subject of interest for utilization of expert knowledge in various control systems over the past two decades. However, their prominence has been put aside in recent years in favour of artificial neural networks, largely due to the abundance of data available for training and the extensive usage of frameworks for rapid solutions deployment.

Despite the dominance of neural networks, there remains space for alternative AI methods such as expert systems, particularly due to their inherent capability to clarify decision-making processes. This paper addresses the need for advanced diagnostics in the industry, focusing on the development of an expert system to assist in diagnosing issues with mobile robotic platforms, represented by the BREACH platform.

While neural networks may seem as the only solution due to their popularity and accessible tool-chains, alternative AI methods like expert systems offer the advantage of backtracking the decision processes, an inherent feature of their design (Zhang, 2019; Bloecher and Alt, 2021; Valerio de Moraes et al., 2022). This capability is even more suited in industrial contexts where the hidden process behind each decisions is as crucial as the decisions themselves. (Korb and Nicholson, 2004; Thrun et al., 2005).

This research is motivated by industry demands, particularly in utilizing the advanced diagnostic capabilities for platforms like BREACH (Krejsa and Vechet, 2018; Vechet, 2011). The development of an advanced diagnostic assistant is based on the necessity to involve maintenance workers, enabling them to address all possible issues efficiently, thereby preventing costly down-times and the need for professional services.

2. Materials and methods

Our experimentation utilizes various autonomous mobile robots, primarily centered around the BREACH platform, developed in collaboration with Bender Robotics. Additionally, the ZALEELA project, aimed

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at indoor plant watering, and the LEELA robot, a lighter version of BREACH, are employed (Vechet et al., 2020). These platforms share common components such as laser range finders, ultrasonic distance sensors, encoders, and motor controllers, all operated using the Robot Operating System (ROS) (Vechet et al., 2020).

	Evidence							
Hypothesis	A - RViz running	B - Map of environment is visible	C2 - Lidar data NOT visible in the map	D - Robot is well localized	D2 - Robot is NOT localized	E - Robots goal properly defined	F2 - Robot is NOT moving	S - Robot rotates in place
D - Lidar (Hokuyo) not connected	✓	✓	✓					
E - Battery low	✓			✓		✓	✓	
G - Robot doesn't boot properly	✓				✓			
A - Encoder not connected								✓
F - Problem with RoboClaw					✓			
B - RoboClaw not connected							✓	

Tab. 1: Attention table which represents the probabilistic model of the machine via the relation between possible hypothesis (problem description) and evidences which can be observed by user.

The mobile robots mentioned above are equipped with standard components such as laser range finders (Hokuyo Lidars), ultrasonic distance sensors (SRFxx), encoders, and motor controllers (RoboClaw), with control software based on the Robot Operating System (ROS) (Vechet et al., 2020).

3. Assistive maintenance

The primary objective of our expert system, named Querix (Vechet and Chen, 2023), is to aid in highlevel maintenance decisions, distinguishing between issues that can be resolved locally and those requiring professional intervention. The further improved solution uses this expert system to identify most probable sources of malfunctions and uses this information to quickly address the possible problem.

Querix operates based on a set of hypotheses and corresponding evidence, utilizing a Bayesian network to model its behavior (Murphy, 2001; Murphy et al., 2001; McGuffin, 2012; Vechet et al., 2016). A limited set of hypothesis and issues was presented in previous work (Vechet and Chen, 2023) and for the reason of limited space we present smaller set of rules condensed into Tab. 1.

Using the hypothesis and evidences outlined in Tab. 1, inference rules are formulated, aiding decisionmaking processes. These rules can be expressed in natural language or in the form of IF-THEN statements (Vechet and Chen, 2023). Tab. 2. provides corresponding conditional probabilities used for decisionmaking.

To compute the probability of possible hypothesis and continue with problem solving the standard Bayes theorem (1) is utilized.

$$P(Hypothesis|Evidences) = \frac{P(Evidences|Hypothesis)P(Hypothesis)}{P(Evidences)} \tag{1}$$

While the conditional probability is common practice in various systems, to naturally get information about the state of the system from knowing some of the evidences about the actual machine status, there is also possibility to use inverse procedure to help the users to identify the possible cause of the system failure from given set of question provided by the system itself. This so called assistive maintenance removes

$P(Evidence|Hypothesis)$

$Hypothesis$	A - RViz running	B - Map of environment is visible	C2 - Lidar data NOT visible in the map	D - Robot is well localized	D2 - Robot is NOT localized	E - Robots goal properly defined	F2 - Robot is NOT moving	S - Robot rotates in place
D - Lidar (Hokuyo) not connected	0.18	0.18	0.18	0.09	0.09	0.09	0.09	0.09
E - Battery low	0.17	0.08	0.08	0.17	0.17	0.17	0.08	0.08
G - Robot doesn't boot properly	0.20	0.10	0.10	0.10	0.10	0.10	0.20	0.10
A - Encoder not connected	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.22
F - Problem with RoboClaw	0.11	0.11	0.11	0.11	0.11	0.11	0.22	0.11
B - RoboClaw not connected	0.11	0.11	0.11	0.11	0.11	0.22	0.11	0.11

Tab. 2: Attention table which represents the probabilistic model of the machine via the relation between possible hypothesis (problem description) and evidences which can be observed by user.

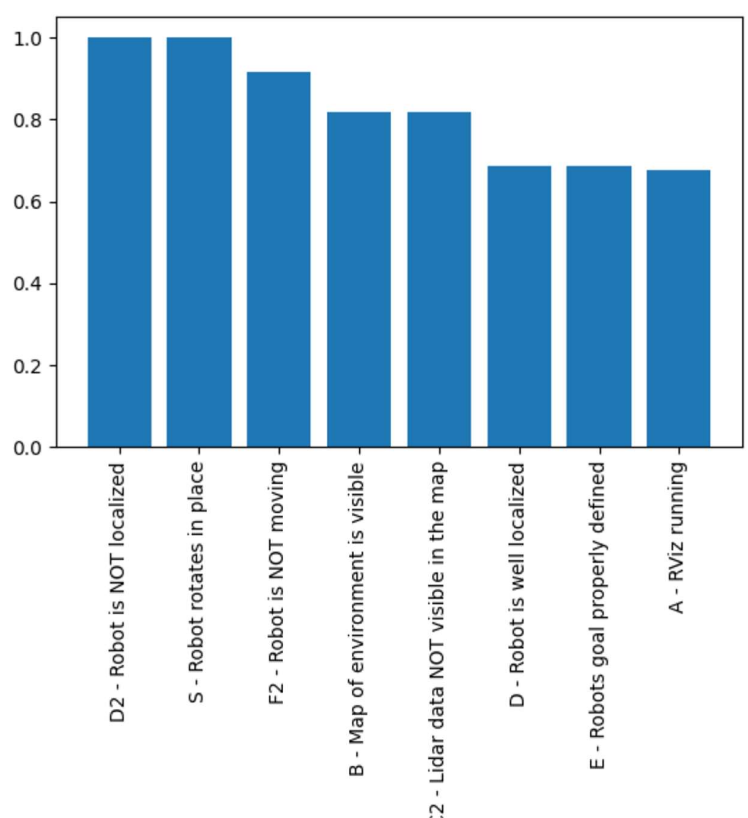

Fig. 1: Most informative evidences calculated for given system of probabilistic rules.

the necessity to call a trained maintenance every-time some problem occurs. To quickly get the right root cause of the systems malfunction the most informative evidences are calculated via Eq. (2). This is the guidance for the expert system what evidence's knowledge leads to the fastest problem identification.

$$mostInformativeFeature = max_{\{i\,=\,1\,:\,m\}}\left[\frac{max_{\{j\,=\,1\,:\,n\}}P(Evidences(j)|Hypothesi\ \ (i))}{min_{\{j\,=\,1\,:\,n\}}P(Evidences(j)|Hypothesis(i))}\right] \tag{2}$$

The list of most informative evidences is shown in Fig. 1 where the results are normalized to have the value for maximum relevance is 1 and it decreases with the relevance for evidence is less informative. This means that when the user provides answer to the most informative evidences the expert system can quickly find the right solution for given problem.

4. Conclusions

The presented expert system, Querix, addresses the need for advanced diagnostics in industrial machinery within the framework of smart factories under Industry 4.0. By developing an inference engine capable of online monitoring, we offer continuous maintenance support to promptly address failures or provide early warnings. The newly added feature of provide the information about most probable causes of failure wider the potential practical usage.

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