Inducing Rules about Distributed Robotic Systems for Fault Detection & Diagnosis

Doctoral Consortium

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ABSTRACT

This paper presents an extended abstract for the PhD topic Inducing Rules about Distributed Robotic Systems for Fault Detection & Diagnosis. The research focuses on developing novel methods for fault detection and diagnosis using explainable machine learning. The main field of application is distributed robotic systems. With current developments in distributed robot technology, the problem of detecting and diagnosing faults becomes more complex.

KEYWORDS

Fault Detection & Diagnosis; Inductive Logic Programming; Explainable Machine Learning; Robotics

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1 INTRODUCTION

Distributed robotic systems are deployed in multiple fields such as autonomous warehouses, production lines or logistic. Distributed robotic systems (or multi-robot systems), can exhibit different behaviours. Robots can behave cooperatively or concurrently. Detecting and diagnosing faults on a singular robot level has its own challenges. In a distributed robot system, the problem of fault detection and diagnosis (FDD) is more complex. Faults can appear on different levels of a robotic system: low-level hardware and software faults, higher-level reasoning and planning faults. In order to maintain safe and continuous operation of robots, faults and failures need to be detected and diagnosed as early as possible.

Machine learning has evolved into an indispensable technique of modern computer systems. One drawback of most machine learning methods is lack of explainability. Explainability should give more insight into a machine learning model, where the model could give the user some explanation with regards to why a decision has been made, what the reasoning behind it is, when and why a method fails. Efforts are already being made in enhancing machine learning methods with regards to explainability such as in [7] and [8].

Another area of research where explainability is at the center of focus is inductive logic programming (ILP) [15]. Models or system descriptions derived by ILP are comprehensible and interpretable since they are in the form of first order predicate rules. What separates ILP from other machine learning methods is the ability to incorporate background knowledge into the learning process.

This PhD is interested in combining methods of FDD with explainable machine learning with a focus on distributed robotic systems. Developing models for FDD is a tedious task and requires expert knowledge. The problem of diagnosis in distributed systems becomes even more complex when considreing all the components within a system. Detecting, isolating and identifying a fault can be costly and cause undesired behaviours to the system. If faults and failures are not diagnosed correctly, the safety and security of the system can be greatly affected. Another problem that has to be considered when developing or learning models for FDD is the hard to find data-sets including faults and failures. For these reasons, developing methods for aiding developers model complex systems more efficiently is paramount.

2 RELATED WORK

In this work, three research fields are relevant and of interest, namely; collection of consistent data from distributed systems, inductuctive logic programming and fault detection and diagnosis.

2.1 Snapshot Recording

In order to be able to learn models, data needs to be collected. Distributed robotic systems produce a large amount of data. The problem with collecting data from distributed systems is consistency. If data collected about the system is inconsistent, then it is not a true representation of the system. Different algorithms already exist to deal with the problem of snapshot recodring [1, 3, 11, 12, 14, 23, 26]. For a more detailed overview of how a distributed system is modelled, refer to [3].

2.2 Inductive Logic Programming

Inductive logic programming (ILP) combines computational logic, programming and machine learning. It has its roots almost 50 years ago in Plotkins [20] research on generalization. ILP systems generate models of systems based on background knowledge (BK), positive and negative examples using first order logic (FOL). Using background knowledge distinctively makes ILP a unique method when learning about systems, since it reasons about facts and statements the same way humans do. Having the ability to invent predicates when needed gives ILP an advantage over current trending methods of machine learning, since they are explainable through BK.

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Alongside advancements in probabilistic logic learning [21], the field of predicate invention and recursion did not advance in a similar manner [16]. In ILP, predicate invention is the process of introducing new predicates during the process of searching for a hypothesis in order to be able to explain the examples. In other words, predicate invention is the process of finding new concepts or theories that are not directly observable from the data. Recursion is used in the process of predicate invention where the problem of finding a hypothesis is recursively broken down to smaller search spaces to explain the examples. Dietterich [4] stated that predicate invention is a fundemental problem in machine learning and that it has an exponentially high complexity. It is also stated that inventing predicates and systematically checking for the significance of each invented predicate is an extremely hard problem. However, advancements have been made in the predicate invention and recursion field which are outlined in [17] and [18] in 2013. The meta-interpretive learner (MIL) is based on inverse entailment for grammatical inference of regular languages. MIL presented an efficient method of implementing predicate invention and recursion for regular and context free grammars via abduction. The invented predicates are introduced as constants that are represented as existentially quantified higher-order variables. Examples derived in MIL are made from a higher-order program, and this results in a first-order program that can be later substituted into the higher-order variables. Meta-rules in MIL can be viewed as program specifications. In order to increase the efficiency of MIL even more, research was conducted in learning Higher-order dyadic Datalog [18]. Datalog is also a declarative logic programming language such as Prolog. Datalog is a subset of Prolog, which is frequently used as a query language. The learning is restricted to the hypothesis space of logic programs where there are at most two variables for each predicate, and in the body up to two atoms. It is shown in the study that H_2^2 is sufficiently general to contain the Universal Turing Machine; therefore, it has sufficient expressibility.

2.3 Fault Detection & Diagnosis

After developing a model of the multi-robot system, fault detection and diagnosis methods are required to deploy the model online and compare observations from the actual system with the model. Applications of machine learning to fault diagnosis of robots already exist [2, 24, 25]. However, the applications are usually used to diagnose specific types of faults using machine learning and require a substantial amount of data to develop an accurate model. It is not easy to find classified data that is specifically for faults in different components. Usually faulty data is disregarded and data sets exist of normal behaviour of components or systems. These are some of the reasons ILP was chosen as a machine learning method for this research. The following publications offer more insight into different methods of FDD [5, 6, 9, 10, 27]. Since ILP is the chosen method for model development, and from the literature on FDD, consistency-based diagnosis, which is part of model-based diagnosis that uses first-order logic to detect and diagnose faults, is a suitable method to be utilized for this project. Founded by Reiters [22], consistency-based diagnosis is used in diagnosing systems by describing the correct behaviour of the components and the way components interact. CBD uses First Order Logic (FOL) to describe the behaviour of the system including its components. A model of a system is then a collection of the FOL statements describing the behaviour of the components. These models are used to diagnose the system based on observations of the real system. Describing a system in terms of its components means that the system can be decomposable, which can help in fault isolation. A description of a system can then be split into three main parts [19]; behaviour of component types, list of components and component structure. Using CBD to diagnose faults in robots has been done previously in different studies [28], [13].

3 APPROACH SUMMARY

To achieve the goals of this research, data sets of multi-robot systems need to be collected. In order to achieve that, a multi-robot system is being developed using actual hardware. Since we are interested in testing and improving the developed algorithms in real scenarios, the development of an actual robotic system is preferred over simulation. Usually in simulation, some aspects are assumed to be noiseless or static, and not all sensor behaviours can be implemented in simulation. Moreover, considering that we would like to later on inject some faults into the system such as cutting off power to some sensors or components and so on, it is more favourable to do so with actual hardware to capture its behaviour using the snapshotting algorithms.

From the data collected, ILP can be utilized to develop explainable models in the form of system descriptions suitable for diagnosis using consistency-based diagnosis. The models can be later deployed to the multi-robot system and diagnosis can be run online.

4 OUTLOOK

The expected outcomes of this research can be summarized as follows: Creation of data-sets of multi-robot system with faults and failures for the purpose of learning faults. Evaluation of state-of-the-art inductive logic programming methods on learning multi-robot system behaviours, from low-level hardware and software components, to complex behaviours and planning. Development of methods to produce explainable system descriptions using ILP, that can be used for consistncy-based diagnosis. Evaluation of developed methods on real multi-robot systems and the effectivness of diagnosing faults and failures.

The PhD project is currently on going and is expected to be completed by 2023. A lab consisting of multiple single-board computer robots that mimic the behaviour of robots in a warehouse environment is currently being set up to collect data that can be used for the later stages of the PhD. Once the data-sets are collected, they will be published along with the findings. The later stages will comprise of utilizing the collected data to produce explainable models of the system, then diagnose faults and failures.

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