Application of agent-based causal-models towards fault diagnosis in mobile robot teams – A feasibility study

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***Abstract*— The purpose of the analysis is to study the feasibility of using an agent-based causal model method (CMM) [1] towards implementing a turn-key solution for fault diagnosis in large teams of heterogeneous mobile robots. The CMM is tested for the following test scenario: project is to demonstrate large numbers (100+) of physical heterogeneous robots cooperating to solve indoor search applications. This project will develop and utilize a number of collaborative control algorithms to enable the robot team to explore an unknown building (one floor), find objects of interest, and "protect" the objects of interest over a 24-hour period, autonomously returning for battery recharging when necessary. The analysis shows that the method is incomplete as a turn-key solution for fault diagnosis in multi-robot teams. The model requires prior knowledge of the faults occurring in the system. The results show that the system performs comparably to behavior-based method that was implemented for the project, if the user if able to model all the faults a priori. The reports highlights two major drawbacks of the method: the model based approach means that as the number of team member increases the system does not scale up very well, also as the system requires modeling of faults beforehand it does not "adapt" very well to environmental changes. In addition, the report details the approach used to evaluate the method and possible measures to overcome the drawback.**

key words: Turn-key solution, multi-agents, causal model, heterogeneous mobile robots, multi-robot teams

I. Introduction

Mobile robots are becoming increasingly useful for military and civilian applications such as urban search and rescue, Future Combat System (FCS) etc. These applications involve complex coordination among various tasks like planning, mapping, localization, formation-keeping, information sharing etc. In order for the system to perform at a high degree of efficiency, it needs to be highly robust. Fault detection and diagnosis is a key feature of robust systems. Fault diagnosis for large tams of robots is an extremely difficult problem. Failures can be caused due to a variety of sensors including faulty sensors, broken equipment, dynamic environments and or other team members.It is especially difficult to diagnose failures in large teams of robots due to the number of components involved in the system.

Toyama and Hager [2] identify robustness as a key challenge in face of uncertainty in complex, dynamic environment for intelligent agents. Atkins [3] describes the inherent explosion of state space complexity in such dynamic environments which inhibits the ability of any designer to specify the correct response in each possible state in advance. Multi-agents have multiple advantages like use of the distributed resources, working in parallel on multiple goals, no single point of failure. The purpose of the report is to consider one such multi-robot solution and attempt to study the possibility of implementing it for a multi-robot team scenario.

Murphy and Carlson [3] identify four important factors in the success of diagnostic system for mobile robots

a. Robustness to noise
b. Ability to deal with uncertainty
c. Efficiency
d. Ability to incorporate information not matter how sparse.

Murphy and Carlson also contend that **turn-key solutions**, solutions that can be applied to a new application without any modifications, are preferred over other approaches, including parameter tuning, for fault diagnosis. In our report we analyze the CMM approach described by Horling, Lesser et al. in [1]. [1] describes the usage of diagnosis towards adaptability for an intelligent home environment. The authors are interested in improving the robustness of multi-agent systems, without compromising efficiency. The paper is a continuation of earlier research by Hudlicka, Lesser et al. [7, 8, 9].

In the analysis we define a sample application in the multi-robot environment called SDR [15]. Our particular application of interest is the deployment of a large number (70+) of simple mobile robots or the follower robots that have microphone sensors to serve as a distributed acoustic sensor network in an complex environment like the one shown in figure 1 . However, due to cost and power considerations, our simple robots have no sensors for localization or obstacle avoidance, and minimal sensing for robot kin recognition (using a crude camera). The objective is to move the simple mobile robots into deployment positions that are optimal for serving as a sensor network. Because these sensor-limited robots cannot navigate safely on their own, we have developed complex heterogeneous teaming behaviors that allow a sensor-rich leader robot, equipped with a laser scanner and camera, to guide the simple robots

Fig. 1. Occupancy grid map showing the object of interest produced during a multi-robot, multiple entry trial: two robots entered from the door at the right top, another two robots entered from the door at the right bottom (the relative pose of the two doorways was unknown). The environment is approximately 45 by 25 meters in size, with an internal area of 600 m2.

(typically, 1-4 of these simple robots at a time) to their planned destinations using a combination of robot chaining and vision-based marker detection for autonomous tele-operation. Due to the large number of robot interactions and the heterogeneous nature of the robots, fault detection and diagnosis are integral for efficient system performance.

II. Related Work

Primary work done in the area of fault detection and diagnosis is still model-based. In recent times, learning based methods are starting to come into prominence. Parker [4] classifies the current state of research in robotics. According to [4] there has not been a lot of research done in the area of multi-robot learning. Inherently cooperative tasks provide challenging domains for learning. On the other hand significant amount of work has been done in the area of agent based learning [5]. Much of the work though is geared towards equipping agents with functions to map the environmental conditions to coordinated actions or using learning to predict the future actions of other agents. There has not been much work done on using learning towards fault detection and diagnosis. The methods that do implement learning for fault-diagnosis, like Nolan and Madden's IFT [6] still depend heavily on models or classified raw data. Wang and Dai [7] uses a control theoretic architecture with each model having its own model/learning- based diagnosis agent. The MML method considered by Carlson and Murphy in [3] appeared to be a model that could be adapted towards mobile robots. Carlson and

Carlson and Murphy [3] evaluate the utility of using Minimum Message Length (MML) technique towards Fault diagnosis in mobile robots. The results of the experiment show that the MML technique did not perform well as a turn-key solution. Based on their experiences Carlson and Murphy also claim that a parameter tuning based approach is also not well suited towards mobile robot fault diagnosis. A parameter-tuning based approach will favor some certain environmental conditions and sensors, thereby limiting its applicability and portability in robotics domain. We use Carlson and Murphy's diagnosis as a basis for our analysis.

The CMM described by Horling, Lesser et al. in [6] is a type of model based parameter tuning approach for fault diagnosis. The CMM was initially designed towards performance issues surrounding the situation specific coordination strategies. In this method the strategy used for agent coordination must be tailored to specifics of the current environment and the coordination situations an agent will encounter.

Kaminka and Tambe present a complimentary approach for monitoring and diagnosis for multi-agent domains called SAM [10]. SAM uses social psychology based fault detection, in which an agent utilizes other agents as a source of information for detecting failures. Social diagnosis is performed by reasoning about failures using an explicit model of teamwork and uses model sharing to alleviate inefficiencies in model representation. Of all the approaches that we have seen, SAM and CMM appear to be the most feasible approach to be implemented for a large multi-robot team environment.

In this report we analyze CMM as opposed to SAM for the following reasons

a. The CMM uses diagnosis as a means to adapt to changes by using a causal model.

b. The causal model is set to handle multiple failures.

c. The diagnosis can be done in a domain-independent manner.

d. The approach described by Horling and Lesser [1] consists of two distinct and independent parts, a TAEMS model that describes the overall model of the system and a causal model that is used for the diagnostic process.

Because of the inherent distributed nature of the test scenario, the system can be broken into two distinct parts, a behavior based model for task allocation and completion, and a fault diagnosis model for detecting and diagnosing the various faults in the system.

III. Method

As mentioned earlier, the original multi-agent model was modified to better fit fault diagnosis for multi-robot teams. The ultimate goal of the research is to identify a turn-key solution for multi-robot fault diagnosis. There has been a lot of research in comparing behavior based with model based methodology for task allocation and completion for multi-robot teams. The original modeled as described by Horling and Lesser consists of two mutually exclusive modules, a goal/task decomposition language called the TAEMS [11] and a structure to describe the pertinent assumptions for diagnosis based on the causal model. The analysis focuses exclusively on implementing the causal model based assumption structure for fault diagnosis. In our earlier research, we have successfully implemented and demonstrated a distributed behavior based structure for the test scenario, Parker et al. [12, 13, 14]. The test results obtained [15] are encouraging. Yet there are a few issues that need to be addressed, primary among which is the influence of fault diagnosis towards overall system efficiency and reliability.

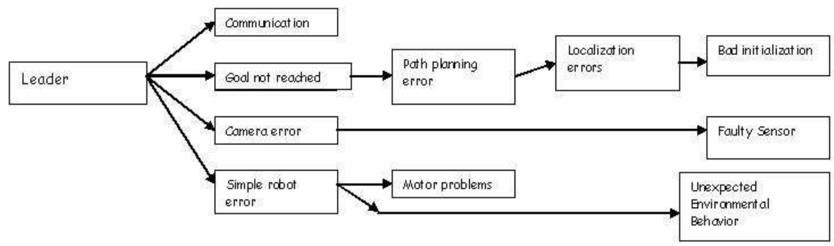

Fig. 2. Pre-Experimental causal model for SDR – based on the failure recovery table from [13]

Thus the focus of this research is to find and implement a generalized framework for a fault diagnosis model.

A. The original multi-agent model

Horling and Lesser focus their research on the performance issues involving situation specific coordination strategies. The model must be tailored to fit the specifics of the environment and the coordination situations the agent will encounter. The model has a base set of assumptions about behaviors and availability of resources that need to be pre-defined. Fault detection is defined as the ability of the agent(s) to recognize when an assumption becomes invalid. Given this invalid assumption, fault diagnosis is defined as the ability of the system to identify the set of resource behavior that is responsible for the failure.

B. Information Requirements

The system needs some prior knowledge about the expected behavior. This baseline behavior serves as a comparison moniker for the subsequent actions of the system. The data can be of three types: knowledge about the agent's expected behavior, methods for detecting deviation, facilities for detecting deviations from those expectations.

C. Underlying Architecture

The model encodes the information/task using a domain independent goal/task decomposition language called TAEMS [11]. TAEMS provides an explicit representation for goals and pathways to achieve them. Method behavior and interactions between other methods and resources are also represented by means of the TAEMS structure. TAEMS provides an organized knowledge structure to be used by the agent(s) for successful task completion. The initial model as designed by Bazzan, Lesser and Xuan [16] focused on designing the diagnosis closely to the underlying system architecture. Based on the work of Sugawara and Lesser [17], the subsequent model used a causal model to organize the diagnostic process in addition to the TAEMS structure.

D. Fault Detection

The original model made use of the information available within the TAEMS structure to detect faults. Within the TAEMS structure, the expected cost, quality and duration values are denoted for each node and relation. The system then uses a comparison monitor to check for deviations from expected value. If a deviation is detected, a flag is set for that error and the diagnosis model is triggered to identify the exact source of the fault. The behavior based model used a similar comparison monitor for checking deviations from expected results via a case-based reasoning structure. A set of rules were defined for the structure, if there was any deviation then a flag was set and diagnosis was performed.

E. Causal Model for Fault diagnosis

The causal model offers greater flexibility in the information it could use and diagnosis it could generate at the same time maintaining domain independence. The causal model for this model is defined as a directed, acyclic graph used for organizing a set of diagnosis nodes [1]. Each node in the graph corresponds with a particular diagnosis with the level of precision increasing from left to right. Figure 2 illustrates the implemented causal model for the test scenario prior to experimentation. As the nodes produce diagnosis, the causal model can be used to find more detailed levels of diagnosis to further categorize the problem. Some of the nodes of the causal model are *triggerable.* These triggerable nodes periodically check for fault, triggering the correlating node in case of detecting one. Multiple faults are handled by means of incorporating a single node for fault that uses the diagnosis of several other nodes for verification. The causal model allows the ease of adding and removing sub-graphs and nodes by the designer depending on the diagnosis specificity required for the system. The designer is also free to make the nodes as domain independent as possible. By making the design as generic as possible, the model can be applied to each one of the agents or robots with little modification. On the other hand, the design of the model is dependent on the individual capabilities, the computation power, sensors etc, of each individual or type of robot in a multi-robot team. Therefore a system can have one or multiple causal models depending on the team composition. In the case of the SDR experiment, the system has one primary causal model, implemented only on the leader robots, due to the computational constraints on the simpler follower robots.

Consider the following example, the follower robot has motor problems and stops. The leader robot periodically monitors the follower robot during the course of transportation and deployment. Over a small period of time the leader robot realizes that the follower is not responding as it is supposed to. It then performs additional tests to have a better idea about the follower's faults. Once it identifies the motor failure as the primary cause for diagnosis, it performs remedial actions which could vary from leaving the follower and carrying on to the next robot to the leader attempting to engage the follower in acoustic detection mode, provided the follower is within an acceptable vicinity of its goal and its other sensors are operational, before carrying on to the next follower.

IV. RESULTS

A. Experimental Setup

The objective of the experiment was to build an autonomous multi-robot system designed to meet a very strict set of requirements that included exploration and map-making of a single story in a large indoor environment, depicted in figure 1, in order to detect a valued object, by deploying a sensor network and to use this network to track intruders and protect the valued objects within the building. This system must also operate autonomously, and employ as *many* robots as possible. These are the specific requirements imposed the DARPA SDR (Software for Distributed Robotics) locate-and-protect mission.

The composition of large robot team, consisting of approximately 80 robots, was mainly composed of relatively simple robots, with minimal sensor and computation capabilities (microphone and a crude camera), a small number of highly capable mapmaking robots and a small group of less-capable leader robots equipped with scanning laser range-finders and cameras. All the robots are equipped with 802.11bWiFi, and a modified ad-hoc routing package (AODV), developed specifically for the SDR experiment, to ensure network connectivity. The initial design of the multi-robot system for SDR used a case based reasoning model for fault diagnosis.

TABLE I

FAILURE STATES DETECTED BY THE LEADER ROBOT AND IMPLEMENTED RECOVERY ACTIONS FROM [15]

Failure Type	**Fault Recovery Action**
Can't reach waypoint	Re-plan path.
Lost simple robot	Leave lost robot in wait state and move on to next robot in chain.
Leader robot camera failure	Leave simple robot(s) in wait state, send camera failure feedback to human operator and return home.
Simple robot motor failure	Check if simple robot is close to goal; if so, change simple robot state to sensor detection and proceed; else, leave simple robot in wait state and proceed.
Localization drift	Check if simple robot is close enough to goal; if so, change simple robot state to sensor detection and proceed; else, leave simple robot in wait state and proceed;
Lost marker	Leave simple robot in wait state and move on to next robot in chain.
Communication failure	Return back home.

Table 1[12, 15] lists the various failure states implemented for the system. Despite the limited number of failure states identified and implemented, the success rate of the leader robots making it back home autonomously in these rigorous experiments was 91% (over 45 trials).

Though the fault diagnosis was implemented by means of a rule-based structure, it can be viewed as a rudimentary causal model with each of the leaf nodes having an appropriate action associated with the corresponding diagnosis. This is depicted in Figure 2. Due to the time constraints a more detailed fault diagnosis could not be implemented for the system. Table 2 depicts the probability of success of each individual module and the overall system probability. Each component/module is designed to be highly reliable, yet due to the overall interaction between the components the overall system probability is only around 50%. In order to make each component highly reliable, each component must be able to identify, recognize and recover from errors.

The causal model can be used to improve the reliability for each module. The main drawback of using causal model is that it depends on the designer to list all possible combination of faults that the system will encounter. Figure 3 denotes the new causal model of all possible errors that could have been designed into the system based on post-experimentation data. Comparing the two causal models in figure 2 and figure 3, we can conclude that it may not be possible for the designer to anticipate and incorporate every possible fault that the system may encounter.This is especially true in case of large multi-robot team environments because of the inherent nature of the domain and the number of moving parts in the system.

V. DISCUSSIONS

The causal model implemented for the experiment, depicted in Figure 2, could have been incorporated with a higher degree of diagnosis, given sufficient time.The point of emphasis though is that it may not be possible for the designer to always predict every possible fault that can occur in the system irrespective of the amount of time involved.

We hypothesize that the experimentation of an integrated technique involving the newer causal model, shown in figure 3, and the behavior based method would still identify faults that can not be diagnosed by the causal model. A minor change in the general characteristic of the environment would result in the designer having to build a completely new causal model. This is an infinitely recursive process that can be proven to be equivalent of an np-complete optimization problem and can never be solved due to the dynamic nature of the environment. The model requires an enormous amount of fine-tuning by the designer for it to be truly robust in a single environment. This prevents the system from ever truly becoming a turn-key solution for fault diagnosis.

On the other hand the causal model provides a good basis for developing a general framework for fault diagnosis that is both domain and architecture independent. The model is currently incomplete as a turn-key solution, but by incorporating distributed learning into the system it may be possible to handle situations that the model did not anticipate. Learning across the team members allows the system to rebuild its

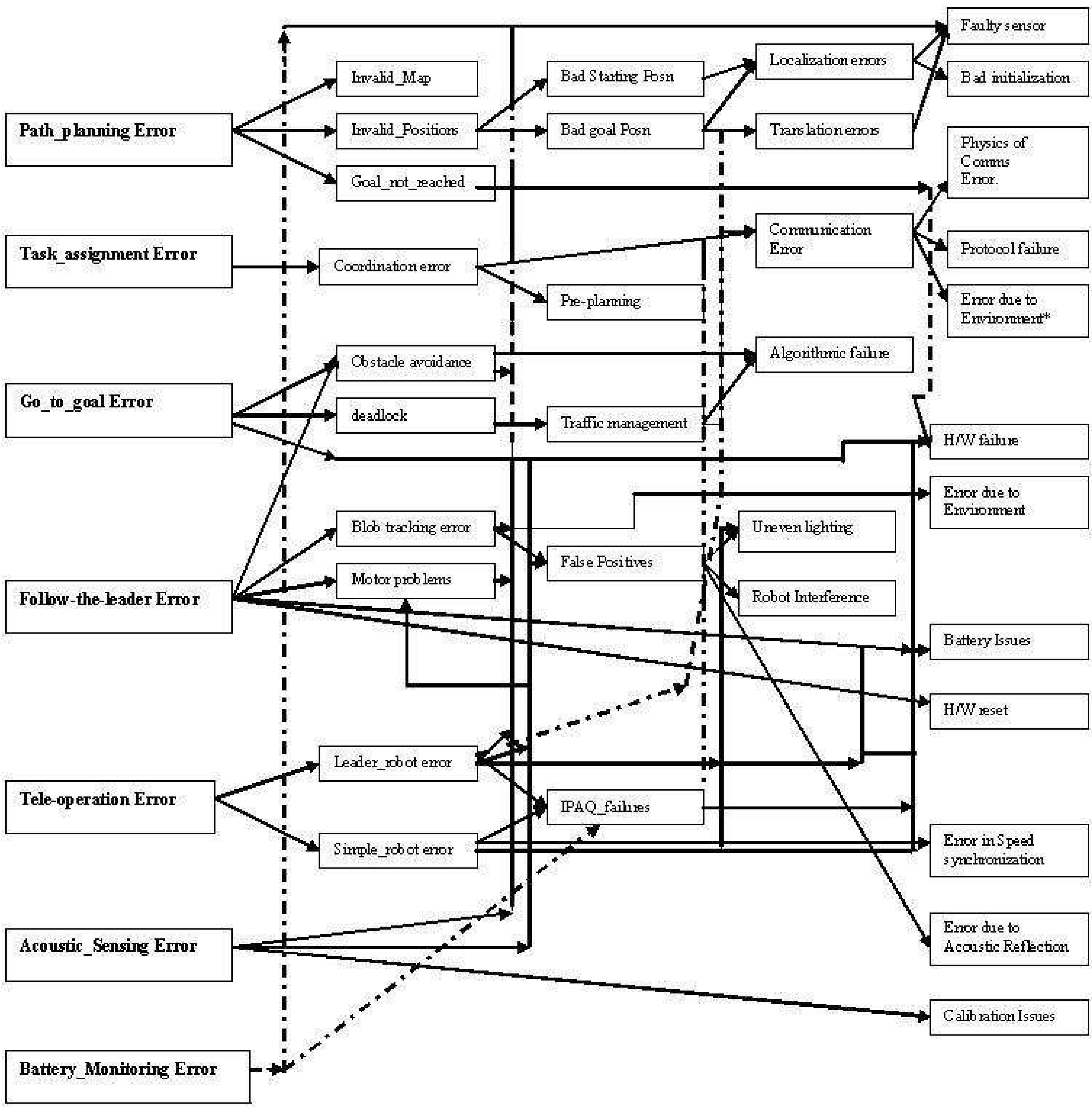

Fig. 3. Post-Experimental causal model for SDR - based on [15]

causal model based on the self and team experience. The focus of our current research is to incorporate the system to learn more about its working environment and as a consequence adapt to it. The specific objectives of learning include:

1) Allowing team members to learn from problems encountered by others
2) Prevent repetition of same tasks that lead to same problems
3) Enable dynamic software re-configurability based on information learned from other team members

This would enable to system to handle situations like bad communications in one area, bad lighting in one area, environment too complex for navigation in one area, blocked passageway without compromising overall system goals of efficiency and reliability. Some of the key issues that are being explored include identifying the type and extent of the learning algorithm required and whether to use single or multiple learning algorithms based on the team composition.

TABLE II

OVERALL SYSTEM SUCCESS RATE, AVERAGED OVER 45 TRIALS

Localization	**Probability**	**Subsystem Success Rate**	**Experimental Success Rate**
Localization	p1	0.83	
Path Planning	p2	0.99 (est.)	
Navigation	p3	0.95 (est.)	
Follow Leader	p4	0.78 (est.)	
Marker Detection	p5	0.98	
Communication	p6	0.91	
Complete System	p1xp2xp3x p4xp5xp6	0.54 (est.)	0.67 (2-robot depl.) 0.48 (1-robot depl.) 0.59 (combined over all trials)

VI. CONCLUSION

The aim of the analysis is to do a feasibility study for using an agent-based causal model method (CMM) [1] towards implementing a turn-key solution for fault diagnosis in large teams of heterogeneous mobile robots. The CMM is applied for a sample multi-robot test scenario. The analysis shows that the CMM method as a turn-key solution for fault diagnosis is incomplete. The causal model depends heavily on the designer's ability to identify and incorporate all possible errors that can be encountered by the system. This is practically impossible for environments in which large teams of multi-robots are deployed. A small variation in the environment would invalidate the entire causal model. The CMM does provide a good basis for building an overall fault diagnosis architecture that is domain and architecture independent. By incorporating learning into the system might allow the system to adapt to the change in environment and to handle faults that were not designed into the original model. We believe that this technique can provide the foundation for developing a turn-key solution for a domain independent fault diagnostic system for multi-robot teams.

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