Agent-based modelling of multi-robot systems

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Abstract. Multi-robot systems can be used in various industrial and non-industrial applications such as manufacturing, environmental monitoring, disaster rescue missions or agricultural foraging. In this context, different problems need to be solved: robot control, robot perception, multi-robot system coordination, global and local planning/re-planning etc. For example, choosing a good coordination mechanism is a difficult task that depends on the application and can be done via trial and error experiments and comparative studies. Some guidelines can be learned from the case studies reported in the literature. Moreover, artificial intelligence provides several techniques (e.g. rule-based systems, machine learning, artificial neural networks, swarm intelligence) that can improve the performances of multi-robot systems coordination. Regarding experimental comparative studies between different methods, a cheaper solution is given by simulations. On the other hand, knowledge sharing between robots can be provided by ontologies that facilitate the inter-robot communication as a base of multi-robot system coordination. Our research work focus on modelling a multi-robot system as an agent based system which is a proper choice for distributed systems and enables simulations. In this paper we present an agent-based model for multi-robot systems that use a common ontology and reinforcement learning as agent adaptation ability. An application for environmental quality monitoring is discussed.

1. Introduction
Several industrial and non-industrial applications require cooperative work of multi-robot systems. Manufacturing, transportation, inspection, maintenance and environmental monitoring are examples of such problems that could be solved more efficiently (i.e. more quickly and robustly than single robots) by groups/teams of robots. As multi-robot systems share a common environment, resources and have inter-dependent tasks to accomplish, a coordination mechanism needs to be defined in order to fulfil the global goal. Usually, each robot has local goals and corresponding specific tasks while within a multi-robot system it has some cooperative tasks to perform. Coordination can be achieved by using various approaches. For example, through direct communication or indirect communication, by partial global planning, organizational structuring, market protocols, contract-net-protocol or by applying different artificial intelligence techniques, either classical (such as knowledge based systems, machine learning) or computational intelligence (such as artificial neural networks, genetic algorithms, swarm intelligence). Choosing the best multi-robot system coordination approach is a difficult task that depends on the particular application and can be done via trial and error experiments and comparative studies. Some guidelines can be learned from the case studies reported in the literature. On the other hand, knowledge sharing between robots can be provided by ontologies that facilitate also the inter-robot communication as a base of multi-robot system coordination. In this paper we present an agent-based...
model for multi-robot systems that use a common ontology and reinforcement learning as agent adaptation ability. An example of application for environmental quality monitoring is discussed.

The paper is structured as follows. Section 2 presents a brief overview of current applications of artificial intelligence in multi-robots systems. Knowledge sharing problem is discussed in section 3 and an upper level OWL ontology, OntoPreMulti-Robot, implemented in Protégé is described. The agent-based model designed for multi-robot systems is introduced in section 4. A case study of using the model for a multi-robot system applied to environmental quality monitoring is also presented. Finally, the last section concludes the paper and highlights some future work.

2. Artificial intelligence and multi-robot systems

Artificial intelligence (AI) provides several techniques and approaches to solve more efficiently applications in which multi-robot systems are involved [1]. Examples of classical AI techniques that were successfully implemented are: rule based systems, case based reasoning, machine learning techniques (e.g. reinforcement learning), while the computational intelligence techniques that were more often applied are: artificial neural networks, genetic algorithms, genetic programming, collective (swarm) intelligence (e.g. ant colony optimization - ACO, particle swarm optimization - PSO). Also, one of the AI approaches most suitable to model and implement multi-robot system is the multi-agent systems approach. In the recent years, swarm robotics based on collective intelligence has been extended more.

We have selected some applications of machine learning, artificial neural network, swarm intelligence, and multi-agent systems in multi-robots systems. The next sub-sections presents a brief overview of them.

2.1. Machine learning

Machine learning can be defined as the capacity of improving the machine’s performance, usually, from experience [2]. Some examples of machine learning techniques are: inductive learning (e.g. decision tree learning, rule learning), reinforcement learning, Bayesian learning, analytical learning. From these, reinforcement learning proved to be suitable for multi-robot coordination. Examples of applications in cooperative multi-robot systems are given in [3], [4], [5], [6] and [7].

2.2. Artificial neural networks

One of the computational intelligence techniques that was implemented in many multi-robot systems for coordination or robot control is artificial neural networks (ANNs) [1]. The ANN types more often implemented are feed forward ANN and time delayed NN. An artificial neural network is based on a biological model and can be defined as a group of nonlinear processing elements (i.e. artificial neurons) which are connected between them (the strength of each connection has an associated weight) and can be structured in layers, in a recurrent or non-recurrent topology. ANNs are usually trained on a training set (during ANN training the weights of the connections are computed) and then the results are validated on a validation set. Examples of some recent applications of ANNs in multi-robot systems are described in [8] and [9].

2.3. Swarm intelligence

Collective intelligence is suitable to solve applications of large size multi-robots systems, as for example robots coordination. The models are copied from natural systems behaviour (usually insects behaviours) and include ant colony optimization (ACO) and particle swarm optimization (PSO). Swarm robotics is one of the most prolific mobile robotics area in which such techniques are fundamental [10]. Examples of swarm intelligence applications in multi-robots systems are discussed in [8], [11], [12], and [13].

2.4. Multi-agent systems

Intelligent agents are physical or virtual entities with autonomy, reactivity, pro-activity and social ability that work in a certain environment characterized as dynamic or static, deterministic or non-deterministic,
open or closed, in order to fulfill a certain goal. Intelligent agents can communicate with other agents in an agent-communication language (e.g. FIPA ACL). Multi-agent systems (MASs) are distributed systems composed of minimum 2 intelligent agents that have a common global goal [14]. The main advantage of an agent-based approach is their capacity to properly model geographically distributed systems. Coordination is a MAS can be achieved with different mechanisms (as e.g. contract net protocol or different negotiation techniques) that provides a coordination protocol and a coordination strategy. Examples of MAS applications in multi-robot system are presented in [6], [9], [15].

Apart from pure AI techniques other methods were applied to cooperative multi-robot systems for robots control or coordination, sometimes in combination with AI. Some examples are given in [16], [17], [18], [19] and [20].

3. Knowledge sharing in multi-robot systems
A multi-robot system can share different knowledge types, as for example, knowledge related to the system structure (i.e. system architectural knowledge and knowledge related to each robot structure), knowledge related to multi-robot system coordination and knowledge from the application domain. Ontologies can provide the technological support for knowledge sharing [21]. They are conceptualizations of certain domains. An ontology is defined by a vocabulary of terms (concepts and relations between concepts) and a set of axioms (restrictions to the use of terms). In a multi-robot system, an ontology provide a common (shared) knowledge used by all robots. The ontology can be used either for inter-robot communication purposes (e.g. by a communication based multi-robot coordination mechanism) or for cooperative tasks execution.

We have designed a preliminary form of an upper ontology for multi-robot systems, OntoPreMulti-Robot that was implemented in Protégé 4.3 as an OWL ontology. The basic concepts of a multi-robot system were defined as classes. Some examples of concepts are: Robot, Sensor, Actuator, RobotAction, Task, Environment, Map, State, EnvironmentMap, RobotState, currentState, avoidObstacle. Also, we have defined data properties (e.g. robotSpeed, robotType, obstacleType) and object properties (e.g. hasSensor, hasActuator, hasBehaviour, hasMap).

Figure 1 shows a part of the ontology class hierarchy.

![OntoPreMulti-Robot ontology class hierarchy (in Protégé 4.3).](image)

The taxonomies of the sub-ontologies associated to the concepts Communication and Robot are given in figure 2 (a) and (b), respectively. Figure 3 shows the graphical representation of some relationships of the Environment and Robot concepts related to their direct dependent concepts (EnvironmentMap, Sensor, Actuator, Behavior) in OntoGraph (Protégé 4.3).
Figure 2. Taxonomies for the sub-ontologies of the concepts Communication (a) and Robot (b).

Figure 3. Graphical representation of some relationships of the Environment and Robot concepts related to their direct dependent concepts (in OntoGraph, Protégé 4.3).

The ontology can be extended with other terms specific to the application domain of the multi-robot system.

4. The multi-agent system model for multi-robot systems
A multi-robot system can be modelled as a multi-agent system by associating to each robot an agent and to the multi-robot system’s supervisor/controller, if exists, an agent. We provide a formal specification of the agent-based model for a multi-robot system and a case study of using the model for a particular application, environmental quality monitoring.

4.1. The formal specification of the multi-agent model for multi-robot systems
A multi-agent system can model a mobile multi-robot system which is a (geographical) distributed system by the set given in (1).

\[
\text{MAS-Multi-RobotSyst} = \{\text{Agents, AP, Tasks, GlobalPlan, SControl, SCoord, Ontology, Goal}\} \quad (1)
\]

where,

- \text{Agents} is the set of agents that model the multi-robot system,
- \text{AP} is a FIPA-compliant agent platform on which the MAS is developed,
Tasks is the set of main tasks required to be performed in order to fulfill the goal of the system, GlobalPlan is the global plan of the system (described in terms of tasks from the Tasks set), SControl is the mechanism of system control (a generic mechanism or a specific one, as e.g. ANN), SCoord is the coordination mechanism applied to the multi-robot system based on agents (a generic coordination mechanism provided by the agent platform, AP, or a specific one, as e.g. FIPA Contract Net Protocol, specific to intelligent agents, reinforcement learning based mechanism or evolutionary swarm robotics with ACO strategy), Ontology is the common ontology used by the agent robots (i.e. OntoPreMulti-Robot ontology extended with terms specific to the domain of application, Goal is the global goal of the system.

Two types of agents are defined: RobotAgent (a cooperative mobile robot agent) and SAgent (the supervisor/global controller agent). The suitable agent architectures are reactive architecture, usually for RobotAgent and a hybrid architecture (i.e. combination between deliberative and reactive architectures) for SAgent. In certain applications some of the robot agents could have a hybrid architecture, too.

Relation (2) specifies the set of agents used in the model.

\[ \text{Agents} = \{\text{RobotAgents}\} \cup \{\text{SAgent}\} \]  

An agent is described by four entities: perceptions (e.g. given by sensors), actions (e.g. executed by actuators), goals (local goals and global goal) and environment (the world in which the agent is embedded). The actions could be primitive or rule based, and single actions or combinations of them provide the tasks performed by an agent.

Each agent has a set of associated tasks, specific tasks (STask) and cooperative tasks (CoopTask). The set of tasks for a robot agent is given by relation (3) and include robot specific tasks (RoTasks as e.g. Navigate) and robot cooperative tasks (RoCoopTasks as e.g. BuildEnvironmentMap when building the map of an environment by cooperating with other mobile robots). The set of tasks for a supervisor agent is given by relation (4) and include supervisor specific tasks (SupSTasks as e.g. VerifyManufacturedProductQuality or Multi-RobotAgentsCoordination) and supervisor cooperative tasks (SupCoopTasks as e.g. GlobalPlanReplanning which involves cooperation with certain robot agents whose local plans are also replanned). The set of tasks of the multi-robot system is thus, defined by relation (5).

\[ \text{RobotAgentTasks} = \{\text{RoTasks}, \text{RoCoopTasks}\} \]  
\[ \text{SupervisorAgentTasks} = \{\text{SupSTasks}, \text{SupCoopTasks}\} \]  
\[ \text{Tasks} = \text{RobotAgentTasks} \cup \text{SupervisorAgentTasks} \]  

The ontology is obtained by merging two ontologies, OntoPreMulti-Robot ontology and a domain ontology, DomainOntology as given by relation (6).

\[ \text{Ontology} = \text{OntologyMerging(O ntoPreMultiRobot, DomainOntology)} \]  

The inter-agent communication by message passing is supported by the agent platform, AP. An example of a FIPA ACL message is given as follows.

\{(inform 
 :content (send-message startEnvironmentExplorationTask area-10) 
 :sender SAgent 
 :receiver RobotAgent-1, RobotAgent-2, RobotAgent-3 
 :ontology OntoPreMulti-Robot 
 :language sl \}

)
A description of the robot agent core in terms of sensors, actuators, robot control, and robot behaviors is provided by relation (7).

\[
\text{RobotAgentCore} = \{\text{Sensors, Actuators, RobotControl, RobotBehaviors}\} \\
\text{(7)}
\]

Some of the robot agents have a reinforcement learning ability of Q-learning type [2] (implemented as a specific robot agent behavior), with the learning function \(Q(.,.)\) given by relation (8). This ability allows them to better perform coordination or cooperative tasks. The basic idea of this learning type is given by a reward or penalty the agent receives when performing the right action or a wrong action.

\[
Q(s, a) = \text{Reward}(s, a) + \gamma V^*(\delta(s, a)) \\
\text{(8)}
\]

where \(s\) is the current state and \(a\) is the action performed in \(s\), the \(\gamma\) factor has values in the interval \([0, 1)\), the state transition function is \(\delta(s,a)\), \(\text{Reward}(.,.)\) is the reward/penalty function and \(V^*\) is the maximum discounted cumulative reward that the robot can obtain starting from state \(s\).

4.2. Case study of using the agent-based multi-robot system for environmental quality monitoring

Suppose we have a multi-robot system composed of 7 mobile robots (R1, R2, ..., R7) and a supervisor computer (S) - a laptop, that has as main task the monitoring of the environmental quality in a geographical area. It is analyzed air pollution status and some potential problems due to air pollution: acid rain and ground ozone which can affect soil quality. The whole multi-robot system is modelled as a multi-agent system as shown in the previous section.

The upper level ontology is extended with some concepts specific to the problem domain (air pollution and meteorology). Some examples of terms specific to the domain ontology (environmental quality monitoring) are: AirPollutant, APConcentration, WarningMessage, AirPollutionEpisode, CO, SO2, NOx, PM10, AirTemp, WindSpeed etc. The limits for the air pollutants are taken from the EU and Romanian Air Quality standards.

Two behaviors related to air pollution monitoring are defined by the Q-learning ability of the robot agents in two air pollution scenarios: acid rain and ground ozone higher levels.

Figure 4 shows the interactions between agents for a given scenario briefly described as follows.

The robot agents R1, R3, R4, R7 are environmental monitoring robot agents which navigate in a certain area, measure some air pollutants concentrations with specific sensors, analyze them, cooperate with other agents (e.g. R3, R4, R7 cooperate with R2 and R6 depending on a particular air pollution episode - acid rain or ground ozone higher levels). The robot agents R2 and R6 are meteorological robot agents that can also navigate, perform measurement of some meteorological parameters (e.g. wind speed, air temperature, relative humidity), and on the basis of the information received from agents R3, R4, R7 and collected meteorological measurements can detect a specific air pollution episode in a certain
sub-area. The R5 robot agent will collect from R2 and R6 the air quality monitoring analysis results, compute the Air Quality Index (AQI) and build a colored map for each sub-area highlighting the air quality status (e.g. green color for no air pollution, yellow color for potential air pollution and red color for higher air pollution).

A general scenario of the agent-based multi-robot system work is described below.

**Scenario:**

R1 – navigation in a certain larger area and detects sub-areas with potential air quality problems (measure the concentration of NOx), communicates with R3, R4 and R7 – send them a message to start measuring the concentration of SO2 and VOC in the sub-areas with NOx higher concentrations;

R2 – navigation in a certain area, meteorological parameters measurement (wind speed, air temperature, relative humidity, precipitations), measurements analysis, communicates with R5 – send a message with the measurements and the analysis result (e.g. possible acid rain or no acid rain);

R3, R4, R7 – navigation in a certain area, measure the average concentration of some air pollutants in a given sub-area (SO2, VOC) and the relative humidity, communicate with R6 (in case of higher values of VOC and SO2 concentrations and lower relative humidity) and with R2 (in case of higher values of SO2 concentrations and higher values of relative humidity) to start meteorological parameters measurement;

R6 – navigation in a certain area, meteorological parameters measurement (wind speed, air temperature, relative humidity, precipitations), measurements analysis, communicates with R5 – send a message with the measurements and the analysis result (e.g. possible ground ozone higher level or no ground ozone);

R5 – navigation in a certain area, receives from R2 and R6 the environmental analysis result and before sending an informing/warning/alert message to S will navigate in the sub-areas with problems and will measure and check the limits of three environmental parameters: PM10, air temperature and NOx, computing AQI, and will generate and send to S a colored map of the sub-areas with problems;

S – supervisor computer – start the multi-robot system environmental quality monitoring in a given larger area (A) by sending a message to R1, communicate with all robots, receive the analysis result from R5 (message and map), build a map of the whole larger area, A, inspected by R1 by integrating the colored maps sent by R5 with green maps for the sub-areas with no environmental quality problems.

Starting from the given scenario a simulated version of the agent-based multi-robot system can be implemented with an agent-based toolkit (as e.g. Jade, Zeus) or with a multi-agents system simulation software (e.g. SeSam).

### 4.3. Discussion on using the OntoPreMulti-Robot ontology for solving some gathering problems

Some typical gathering problems encountered in multi-robot systems are simultaneous localization, and path planning. In these cases, the inter-robot communication via messages will facilitate the problem solving. The messages will contain concepts from the ontology of the agent-based multi-robot system, OntoPreMulti-Robot. For example, in the case of simultaneous localization, the robot agents will be synchronized by a start message to receive simultaneously information from sensors that provide their position and to exchange them via message passing with other robot agents. In the case of path planning problem, the robot agents will exchange messages with information related to obstacle/wall detection and further command, avoid obstacle/follow wall or to the specific path searching algorithm (e.g. A*).

### 5. Conclusion

Multi-robot systems can be efficient in solving different distributed cooperative tasks such as industrial manufacturing, environmental quality monitoring (e.g. to detect severe air pollution episodes due to industrial activity or to detect higher levels of radioactivity in case of nuclear accidents), calamity rescue operations (e.g. natural calamity in case of earthquake - to detect the presence of life via infrared sensors, industrial disaster in the mining industry - to detect human presence or dangerous gases in order to prevent accidents), and agriculture foraging. The higher complexity of such systems can be tackled in a
proper way by a multi-agent modelling approach which is suitable to develop geographically distributed systems. We have presented an agent-based model for multi-robot systems which facilitates inter-robot communication by using a common ontology and reinforcement learning ability to improve robots’ coordination performance. A case study of environmental quality monitoring with an agent-based multi-robot system was analyzed in order to show how the multi-agent system model is working.

As a future work we shall implement as a simulation the agent-based model of a multi-robot system for environmental quality monitoring and we shall perform comparative studies of different multi-agent system coordination techniques.

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