Multi-variant Planning for Dynamic Problems with Agent-based Signal Modeling

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Abstract
The problem of planning for groups of autonomous beings is gaining attention over the last few years. Real life tasks, like mobile robots coordination or urban traffic management, need robust and flexible solutions. In this paper a new approach to the problem of multi-variant planning in such systems is presented. It assumes use of simple reactive controllers by the beings, however the state observation is enriched by dynamically updated model, which contains planning results. The approach gives promising results in the considered use case, which is the Multi Robot Task Allocation problem.

Keywords: planning, agent systems, mobile robot management

1 Introduction
Planning for groups of beings coexisting in common environment is becoming a very important research area. New solutions can improve effectiveness of many real-life systems, where large number of independent beings execute their tasks, causing conflicts or collaboration needs. In many cases the behavior of the beings cannot be precisely predicted or controlled, which significantly complicates the planning tasks. Moreover, many processes require very fast execution, leaving little time for planning or re-planning.

Real-life examples of such processes include network routing, urban traffic management or mobile robot coordination. In network routing systems large number of devices collaborate to provide the highest possible quality of service. Unexpected situations concerning device failures, delay or traffic intensity cannot be precisely predicted and should be handled within milliseconds. In case of urban traffic control the need for detecting and handling unexpected situations is even more important, as safety of traffic participants depends on it.

The problem of mobile robots coordination can be considered in different applications, like motion planning, formation control or task assignment [4]. All these problems share similar features. Planning algorithms are typically complex and time consuming and the plan execution
process is often altered by unexpected situations. The problem of Multi-Robot Task Allocation (MRTA) will be used as an example in this paper.

Classical artificial intelligence [8] does not provide dedicated solutions to the described class of problems. Typically planning for multiple beings is reduced to the classical planning problem with large dimensionality of the search space. Detailed analysis of existing approaches to the problem of planning for multiple beings (presented in the next section) leads to the following conclusions:

- The problems of planning actions of multiple beings are complex, therefore finding (sub)optimal plans is a time-consuming process.
- Scalability of the solutions based on complex algorithms is very limited.
- Most of the solutions return only one, (sub)optimal plan, which results in significant problems with robustness. When the plan execution fails the system can become very inefficient because of the need of costly replanning.

These issues suggest looking for different approach to the specified problem, which is designing a reactive (behavioral) controllers [1] for the beings. The controller is a set of rules which are triggered by observation of the environment. Subsequent decisions allow the beings to eventually reach desired state. Reactive controllers make it possible to create large scale, robust systems, which can successfully cope with inaccurate execution of orders or unexpected changes in the problem itself.

Putting flexibility over performance, the reactive systems suffer from different set of issues, like inability to guarantee completeness or predict task execution time. Moreover, it is not always possible to create a reactive controller for a complex coordination problem – simple observation of current environment state may be insufficient.

In this paper we propose a new approach to the problem of controlling the behavior of multiple coexisting beings. It aims at providing flexibility of behavioral controllers together with the ability of using intelligent planning. The approach is based on the concept of using intelligent model of the environment at the decision making stage. The intelligent model is composed of software agents, which represent, exchange and expand knowledge about the environment and the problem to be solved. The software agent paradigm applied widely in various domains [2], seems very well suited for solving problems of managing multi-robot systems [11, 10].

The agent system constructing the environment model represents the distributed planning intelligence of the system. A set of dedicated agents knows possible actions in particular states of the beings. Interactions in the agent system itself lead to spreading information about possible actions' evaluation. This information is used by the beings for making decisions. Different decisions in particular state are available, resulting in multiple variants of behavior for each entity. Therefore, the agent system provides the beings with the multi-variant plans.

The mechanism of spreading information in the agent system is inspired by biological signals observed in the real world, like smell or sound. The concept has been used in [15, 9], where simplified signal spreading algorithm has been presented.

In this paper we introduce the new concept of model intelligence represented by various types of agents creating the model. We also present the application of the method for the Multi-Robot Task Allocation problem, which has been implemented and tested using a 3D mobile robot simulation system.
2 Planing for Dynamic Problems

The considered problem of planning for multiple beings actions can be addressed with various methods. Classical approach comprises AI planning, domain-independent planning as in [8], where the search space is related to planning for all beings at once making the joined state.

Domain-independent planning has received significant attention since the 1980s [13]. It is still being researched focusing on heuristic functions and methods for constructing new heuristic functions [5]. These approaches are often used in the robotics domain where simple path planning problems are considered [6]. Different planning algorithms provide optimal or sub-optimal solutions to the given problem, however, they deliver one plan only, which does not include variants.

There is also a group of methods which assume the partial lack of knowledge needed for a planning being to establish the optimal plan. Such an approach is called planning under uncertainty, and it takes into consideration dynamic changes in the problem configuration. Uncertainty modeling is the basis of solutions in this case, and the way of modeling can fall into one of four categories as proposed in [7]: conceptual models, analytical models, AI-based models and simulation models. Probabilistic reasoning, predicting possible situations using probability distributions are usually used to solve the above-mentioned problems.

The particular problem considered in this paper, which is Multi-Robot Task Allocation (MRTA) has been solved mostly using centralized and distributed methods.

There are two basic types of approaches towards MRTA problems: centralized and decentralized ones. Complexity of the problem, which results from the considered variant, decides on different optimization algorithms to be used for calculating the best allocation.

The algorithm needs knowledge about the environment, as well as robots and tasks, which require intensive communication. Centralized solutions use single algorithm executed on a single computer to make all decisions concerning the allocation of robots to tasks. In most cases this includes choice of a leader of the group [3]. Centralized approach can in theory give the best i.e. closest to optimal results. However several properties of this method, e.g. single point of failure, very intensive communications and inability to react fast for changes, have implied focusing on decentralized approach. There are many variants of distributed algorithms that have been proposed to conquer these problems. They are mostly based on predefined negotiation protocols, which determine what information is to be exchanged and what robots’ reaction should be in given situations [17]. Such solutions do not possess a single failure point, but they still suffer from compound communication protocols and do not react on changes quickly.

There is a group of solutions that solve the allocation task with no obvious communication between robots. Then, decisions of them are based on observation of other robots and an environment, as e.g. the low-level task assignment in [16]). Such swarm solutions are more robust. Functioning of the system is not endangered by a single robot failure. However creation of a fully autonomous algorithm for a complex task of the class of MRTA is not direct.

The method presented in this paper uses a behavioral controller for calculating decisions of particular entities in given situations. However the input for the controller is not fully determined by observation of the real environment surrounding the being. It is also derived from a model of the environment created and updated by an agent system. The model represents multi-variant plans keeping flexibility, durability and scalability. Introducing intelligent agents into the model makes it possible to include complex planning.
3 Agent-based Model of Information Transfer

One of application areas of intelligent systems is management of groups of collaborating mobile robots (mobile robots systems) or more general mobile being systems.

We can consider two basic elements in such systems - a group of mobile beings and an environment, where these beings act. The mentioned beings may move in the environment and change it, what enables execution of tasks which occur in the environment. We assume that tasks appear at random in the environment and their parameters are also unpredictable. It creates a situation, that environment of mobile being actions changes dynamically what makes planning actions of mobile beings much more difficult.

Management of mobile beings may be considered as realization of two tasks, namely a strategic aim concerning actions of beings’ group as a whole and tactical goals concerning actions of a given being (or beings’ subgroup) within a group.

Strategic management should be realized as an intelligent one, with planning complex tasks and applying global view on an environment, while tactical approach requires to be reactive, behavioral and based on simple observations of the environment. A system using a model driven approach should be considered to realize such a management. This model-driven approach is based on the following idea: in the cyberspace there is a model of the mentioned system of mobile-beings acting in the real space. This model in the cyberspace comprises an environment model and models of beings that are realized as agents. So, the whole mobile-beings system (e.g. mobile-robots system) is modeled in the cyberspace as an agent system.

As a result we have a real environment and mobile beings acting in it and its model composed of a virtual environment in the cyberspace, and agents modeling beings’ behavior.

The virtual environment created this way may be enriched with properties which do not occur in the real environment i.e. we build the so-called enhanced model. Introducing the enhanced model enables easier and more efficient management of the mobile beings in the real environment.

Since parameters of the real environment change in an unpredictable and dynamic way, to realize the strategic goals, it is necessary to prepare several versions of a plan which leads to the multi-variant planning approach.

The most often used models of robots’ environments are different types of graphs. The nodes are places where agents may reside and where resources are located, as well as tasks for realization. The edges define a structure of the graph environment, creating relation between nodes (neighborhood) or transition between states.

To realize strategic planning by tactical actions, agents should have ability of acquiring the more detail information. This information is about this part of environment where a given agent remains and in a more general form about its neighbourhood.

To acquire such information we propose the method of signals spreading. The signal can be used to carry information between agents, and between agents and environment resources. We can observe different ways of realization of transfer of signals in a given environment. The domain of robotics has already applied some methods using signal dissemination in the virtual space like a diffusion of medium such as odor (pheromone in the ant systems) [9] or sounds (ultrasounds in bat systems [14]).

The medium may be generated by some elements of the system (e.g. tasks) and received by others elements (e.g. agents) which are going to manage tasks execution. Distribution of medium is defined by appropriate rules, like diffusion defined in physics, resulting in the medium is transferred from a part of the environment where there is higher intensity of the medium to neighbor places where the intensity of the medium is lower. Such approach can be compared to
concept of gradient or potential field methods. However, simple rules are insufficient in complex
coordination problems because they do not guarantee completeness.

The idea presented in this work involves more intelligent rules of transferring information,
which can be compared to "gossiping". For this purpose it is necessary to provide the system
with entities realizing operation of "gossiping". In the virtual environment an appropriate
agent, called $a_i$, plays such a role (index $i$ enables identification of the agent in the agent system).

Summarizing the dissemination of the information may be realized as follows (fig. 1):

- Agent $a_i$ is responsible for particular fragment of the environment.
- Given agent $a_i$ obtains information (a signal) sent by one of neighboring agents.
- Agent $a_i$ decides when and where to send this information (a signal).

![Figure 1: Schema of exemplary transfer of gossip among agents.](image)

Such a way resembles dissemination of a gossip in a society. Agent $a_i$ choosing a receiver for
the transferred signal can realize a kind of "intelligence" of the process of information distri-
bution in the system. It results in non-uniform distribution of information in the environment
which is a multi-variant plan. Every agent can have several different variants of information
received from different sources.

4 Implementation for the Multi-Robot Task Allocation Problem

The exemplary problem used for testing the proposed approach is the Multi-Robot Task Al-
location, where a group of mobile robots has to be assigned to a set of tasks located in the
environment. Various variants of the problem have been considered by researchers [4], differing
in the level of dynamics. In our tests we assume that the tasks can appear on random basis
in random locations in the environment. Such assumption makes all time-demanding planning
solution useless.

The agent system, representing the model of the environment, covers the workspace of
robots by assigning equal square areas to individual agents. Each agent has 8 direct neighbors
it can communicate with (agents on at the edge of the environment can have less). Each agent
processes signals of eight directions, each pointing a neighbor area. The direction with the
highest value of signal is considered most attractive for robots. There are two basic sources of signal: tasks and robots.

Depending on the type of the environment fragment and its current state, the agent will have a different strategy concerning signal propagation, generation and attenuation. Once an agent detects a task in the assigned environment area, it starts to generate attracting signal to all its neighbors (Figure 2a.). When a robot enters the area, the agent emits negative (repelling) signal.

Over the time the agents exchange (propagate) the information about the signal. The basic signal propagation rules in the lattice of agents is presented in Figure 2b.

The normal signal (vertical and horizontal directions) is passed forward, while the diagonal signal spreads to three directions. Putting the propagation rules more formally, we can say that each agent \( a_{n,m} \in A \) representing cell \( n, m \) of the lattice, stores a vector \( as \) of eight significant real-valued signal information:

\[
  as_{x,y}^{n,m} \quad \text{for} \quad x \in \{-1, 0, 1\}, \quad y \in \{-1, 0, 1\} \quad (as^{0,0}_{n,m} \text{ is skipped})
\]  

The value \( as_{i,j}^{n,m} \) represents the attractor strength of the agent \( a_{n+i,m+j} \).

The basic propagation rule, presented in in Figure 2b. can be reduced to the following propagation function \( P \):

\[
P(as_{x,y}^{n,m}) = \begin{cases} 
  as_{x,y}^{x+n,x+n+y}, & x \neq 0 \land y \neq 0 \\
  x-y, & x+y, x-y, x+y, x-y, x+y
\end{cases}
\]  

This method of exchanging the signal between agents results in uniform distribution of the signal in the model. The effect of signal differentiation has been achieved by adding signal memory and attenuation. The propagated value from a neighbor agent is added to the current value of the agent. Calculated value is reduced according to a given attenuation factor. This results in signal strength distribution dependent on distance from detected tasks.

The problem of obstacles in the environment has been addressed using the application of different propagation strategies. A disabled agent representing inaccessible fragment if the environment neither accepts nor distributes signal propagation information (Fig. reffig:difract).

The above-mentioned algorithm for signal propagation needs additional rules for distributing signals behind obstacles. The proposed solution is inspired by the diffraction phenomenon and
Figure 3: Diagonal (a.) and normal (b.) signal diffraction (the dotted arrows) implemented by agents propagation behaviors.

is implemented by an agent located next to a disabled agent. The simple rules of adding one diagonal propagation message (marked as dotted arrow in Figure 3) is sufficient to cover whole environment with signal.

The presented rules of signal generation, propagation and attenuation are sufficient for solving the MRTA problem successfully, which will be shown in the next section. Each of the robots executes the same, fully reactive algorithm. In the first stage of each step the robot checks distance sensors readings to find out if a sudden turn or emergency stopping is required. If not, the agent representing the robot contacts the agent responsible for the current robot’s location and collects its $a$s vector. The angular velocity of the robot is set for a value proportional to the angle between robot’s orientation and the direction of the strongest attractor signal.

The agent-based environment model has been further enriched with additional behaviors of agents. In order to improve distribution of robots in the environment the repeller pushing behavior has been proposed. When an agent detects a robot in its assigned area it generates a repelling signal in order to discourage other robots. The repeller pushing behavior also analyze the velocity of the robot and notifies agents in front of the robot to generate proper repelling signal. The difference is presented in Figure 4a.

Figure 4: The repeller pushing behavior (a.): one the left no pushing is used, on the right the signal is generated in front of the moving robot. The signal generated by a directional emitter located (b.)
Another interesting behavior which has been tested was the **directional emitter**. The strategy of an agent located in a narrow passage has been modified so that it constantly generated attracting signal from one side of the passage and repelling from the other. The generated is presented in Figure 4b. Properly located emitters encourage robots to circulate in the environment, which turned out to improve the performance of the MRTA solution.

Many other behaviors of the agents in the environment model can be easily added in order to improve the performance or solve particular situations in the system. The greatest advantage of the approach is that the robot controller remains very simple and fully reactive, which guarantees flexibility and robustness of the system.

## 5 Experiments and Results

The experiments on the created implementation of the solution have been carried out using the RoBOSS simulator [12]. The simulator makes it possible to define arbitrary shape of the environment and various types of mobile robots. It can cooperate with client programs connected via network interfaces, which simplified implementation of reactive controllers and the agent system.

In order to compare the developed solution with other approaches, two other algorithms have been implemented. The first, fully distributed algorithm with autonomous greedy approach, where each robot pursues the closest task. The algorithm continuously leads to situations where several robots approach the same task, which is far from optimal. The second algorithm was fully centralized with allocated tasks to robots calculating minimal sum of distances.

Both algorithms are provided as reference points for the tested solution. The proposed reactive approach cannot be better than the centralized planner and should not be worse than the distributed greedy algorithm.

The first test environment was a single rectangular room (Figure 5a.), where four robots were supposed to reach locations of appearing tasks. There were four tasks simultaneously present in the environment. After a task was finished, a new one was immediately created in a random location.

![Figure 5: Two environments used in the experiments. On the left: two visualizations of the basic scenario with four robots. On the right: the environment divided into four connected spaces.](image)

Each experiment has been conducted until 1000 tasks were fulfilled. The average time of
reaching a task for all three methods is shown in Table 1.

|                  | autonomous-greedy | centralized-planning | multi-variant |
|------------------|-------------------|-----------------------|---------------|
| time             | 5.9 s             | 2.8 s                 | 4.8 s         |

Table 1: Results of the MRTA experiments with four robots.

The multi-variant method provided results significantly better than the autonomous greedy approach. During the execution proper behaviors of robots splitting a group in order to reach different tasks were often observed.

More complicated environment with four rooms (Figure 5b.) showed the advantages of the solution even better. Both the autonomous-greedy and centralized-planning method failed to provide proper operation because of lack of required navigation method – finding doorways leading to desired tasks would require another algorithm. On the other hand it turned out that the multi-variant method provides a robust navigation method automatically, without any modifications to the algorithm.

Table 2 shows the results of two versions of the multi-variant algorithm. The basic version is compared to the version enriched with directional four emitter located in all doors, which provoked robots’ circulation.

|                  | basic multi-variant | multi-variant with emitters |
|------------------|---------------------|----------------------------|
| time             | 4.9 s               | 4.2 s                      |

Table 2: Results for the multi-variant method in complex environment.

The results show two interesting features of the solution. The first is that the presence of the obstacles does not influence the results significantly. The second is the improvement of the performance after adding the directional emitters. It turned out that constantly moving robots locate tasks faster than robots waiting for tasks to appear. Further experiments are needed to explain this phenomenon.

6 Conclusions

Planning for multiple beings coexistent in common environment is a significant problem which will probably gain importance. Scalable and robust solutions will be needed to solve real-life problems of robot coordination or traffic management.

The approach presented in this paper gives very promising results. Combination of behavioral controllers of autonomous beings, planning intelligence in separated model layer and agent-based implementation offer a set of very desirable features. Obtaining coordinated behaviors of beings without continuous and explicit communication seem a significant achievement.

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