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Review for Collective Problem-Solving by a Group of Robots

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Abstract:

This article discusses the relevance of using a group of robots to solve various problems. It was also revealed that despite the obvious advantages of this approach, it causes certain problems in its implementation. The authors address some of these problems and offer possible solutions to them.

Key words: Mobile Robot, Adaptation, Robot Control System, Manufacturing Innovation, Industrial Innovation.

Introduction

The execution of intricate tasks presents a challenge for individual robots due to their limited capabilities and time constraints. Robot systems are widely used in industry [1]-[8], logistics [9]-[17], agriculture [18]-[20], medicine [21]-[24] and other areas, where they help solve complex problems, increase productivity and reduce costs. And here various methods and approaches can be used [25]-[35].

However, by collaborating, robots can leverage their unique skills to successfully tackle complex tasks, including joint assembly, coordinated transportation, and simultaneous monitoring of multiple parameters.

The use of groups of robots (or multi-robot systems) is becoming increasingly relevant in modern technology and industry.

The relevance of using groups of robots is due to a combination of technological progress, economic factors and the need to improve the safety and efficiency of various processes. For various reasons, the significance of collective problem solving by a group of robots is growing in importance within the field of modern industry. Collaboration between robots offers a lot of benefits in terms of efficiency and

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scalability. By delegating tasks among a group of robots, industries can increase productivity, accelerate work processes, and effectively manage heavy workloads. By employing a team of robots, the system becomes more sustainable, as the failure or obstruction of one robot does not stop productivity. Instead, the remaining robots can seamlessly carry on with the tasks at hand, minimizing downtime and guaranteeing the uninterrupted flow of industrial operations. In real-time, these robotic teams can collaborate, reconfigure, and coordinate their actions to optimize tasks according to changing conditions.

By working together, robotic systems have the capability to enhance the precision and reliability of various industrial processes. This collaborative approach significantly reduces errors, rework, and material waste, ultimately leading to an overall improvement in product quality and substantial cost savings.

The ability to make decisions in real time is crucial in dynamic industrial settings that demand quick adaptation and response. Systems that involve multiple robots have the capacity to display unpredictable behavior and autonomously organize themselves to collectively make decisions. This capability proves to be highly valuable in environments where rapid adjustments are necessary. Advances in collective robotics, swarm intelligence, and distributed control algorithms are driving innovation in industrial automation. Industries are exploring new applications such as cluster-based manufacturing, collaborative human-machine interaction and autonomous material handling systems to improve operational efficiency and competitiveness.

All things considered, industries today are changing as a result of a group of robots working together to solve problems and produce more effective, adaptive, and flexible automation solutions. The future of manufacturing, logistics, and other industries will be greatly influenced by the collaborative skills of robotic teams as these businesses continue to adopt robotics and artificial intelligence.

Related works

Using a group of robots to solve various problems has both a number of advantages and a number of problems associated with the complexity of coordinating the work of various robots. Many scientists devote their work to studying such problems. Let's look at some of these works.

In [36] authors review the unique roles robots can play in groups, finding that small changes in their nonverbal behavior and personality impacts group behavior and, by extension, influences ongoing interpersonal interactions.

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The article [37] presents a review about mobile robot navigation problem and multimobile robotic systems control. The main focus is made on path planning strategies and algorithms in static and dynamic environments. A classification on mobile robots path planning has been defined in the literature and divided to classical and heuristic approaches.

In recent years, the use of Multi-Robot Systems (MRS) has spread, consisting of both Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs), gaining versatility and robustness in their operation [38]. The possibility of using heterogeneous robotic teams allows tacking, autonomously, and simultaneously, a wide range of tasks with different characteristics in the same environment. Authors note, that path planning becomes a crucial aspect.

Multi-robot systems usually refer to a group of fixed/mobile robots with sensing, computation, communication, and actuation capabilities that enable them to accomplish certain tasks cooperatively in a distributed mode [39]. Researchers consider problem of coordination of these multiple robots, that needs systematic methodologies to design and analyze cooperative strategies to control multi-robot systems.

Paper [40] asserts that multiagent robotics playing a prominent role both as a canonical instantiation of a system, where control decisions must be made by individual nodes across an information-exchange network, and as a rich source of applications.

Scientists in [41] present Kimera–Multi , a multi-robot system/ This system is is robust and capable of identifying and rejecting incorrect inter- and intrarobot loop closures resulting from perceptual aliasing; fully distributed and only relies on local (peer-to-peer) communication to achieve distributed localization and mapping; and builds a globally consistent metric-semantic 3-D mesh model of the environment in real time, where faces of the mesh are annotated with semantic labels.

So we see that combining several robots into work leads to the emergence of new challenges, to the emergence of new problems in organizing their work, in controlling these robots.

Robot team work. Review of main issues

Collective problem solving by a team of robots involves multiple robots working together to solve complex tasks or achieve a common goal. This approach draws inspiration from cooperative behaviors observed in nature, such as social insects (e.g., ants, bees) or bird flocks, where collective intelligence arises from interactions between

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individuals. Next, the key aspects of collective problem solving with the help of robotic groups will be presented.

First of all, we should talk about distributed task allocation. There are different types of tasks that are dynamically arriving to a system. Each of the agents can satisfy only a subset of the tasks. The main goal of the agents is to maximize the overall performance of the system and to fulfill the tasks as soon as possible. The agents are modeled using a stochastic closed queueing network. The problem is divided into two subproblems: to determine a distributed policy of optimal task distribution and to find the optimal effort levels of the agents subject to certain constraints. For the first subproblem, a distributed polynomial allocation algorithm for determining an instantaneous probabilistic optimal policy for task allocation is presented. The policy is independent of the state of the system and thus does not require information exchange among the agents during the performance of the tasks. For the second subproblem, an analytical solution to find the optimal effort levels for the agents are given.

Second key aspect of collective problem solving is collaborative sensing and information sharing: Collaborative sensing is a process that combines and utilizes resources from different physical or virtual devices to deal with complex sensing problems. Conventionally, large-scale physical environments are monitored using multiple homogeneous or heterogeneous sensing devices, pre-deployed in different places. For example, pre-deployed cameras and magnetic sensors compose collaborative networks for traffic monitoring and control. So, robots can share sensing information and observations with each other to jointly build a comprehensive understanding of the environment. This shared information can be used for decision-making, path planning, or problem solving. For example, robots equipped with cameras or sensors can exchange real-time data about obstacles, targets or hazards.

Emergent behavior and self-organization also have a great impact on collective problem solving. Model grouping in the known multiagent systems consuming the agents connections topology time evolution is an incredible tool for studying complex stochastic systems. Here, the agent notion may correspond to some dynamical model (a system component) or a specific set of models. Without rigid centralization, these structures can successfully treat complex problems by splitting them into modules reallocating the agents’ dynamical partitions. Such a system can effectively perform under significant uncertainties, demonstrating so-named “emergent intelligence”. This notion signifies an intellectual resonance or a swarm intelligence consisting of the

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manifestation of unexpected properties of the whole system not inherent to any simple element.

The critical feature of emergent intelligence consists of the dynamics and unpredictability of the decision-making process. In practice, this means that the solution is achieved at the expense of hundreds and thousands of untraceable interactions. The desirable protocols are generated and executed by the agents themselves. At each step, they ponder the system inputs and respond to unpredictable events such as delays and crashes. Thus, emergent intelligence is a new superior unique factor arising, as it were, "out of thin air" due to many hidden or explicit conditions spontaneously appearing and disappearing in the system.

Robots also must coordinate their motion and actions to effectively achieve a common goal. This coordination can be achieved through decentralized control algorithms, where a robot communicates and negotiates with nearby neighbors to adjust its behavior. For example, maintaining formation, navigating in crowded environments, or transporting objects together.

Adapt to dynamic environments. In order to solve collective problems, robots must be able to change course when necessary or react unexpectedly to outside occurrences. Robust performance in complex and uncertain contexts necessitates adaptability. Understanding the need to adapt robots, it is important to know how to teach robots to adapt to a dynamic and uncertain environment.

Reinforcement learning (RL) is one of the most widely used and effective methods for teaching robots to adapt to dynamic and unpredictable surroundings. Robots can learn by their own behaviors and feedback thanks to reinforcement learning (RL), a subfield of machine learning, which eliminates the need for direct supervision or instructions. Robots may explore their surroundings, try out various activities, and get rewarded or penalized depending on how things work thanks to reinforcement learning algorithms. Robots can learn to carry out actions that are in line with their objectives – such as arriving at a specific area, dodging obstacles, or handling objects – by maximizing their reward function.

Another important aspect of training robots to adapt to dynamic and uncertain environments is human-robot interaction (HRI). HRI is the study of how humans and robots communicate, collaborate, and coexist in shared spaces. HRI methods can help robots to learn from human guidance, feedback, demonstration, or imitation, as well as to understand human intentions, emotions, and social cues.

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A third method to train robots to adapt to dynamic and uncertain environments is transfer learning (TL). TL is a technique that allows robots to leverage their existing knowledge and skills to learn new tasks or domains, without requiring extensive retraining or data collection. TL can help robots to generalize their abilities across different scenarios, such as changing environments, objects, or goals, by transferring relevant information or policies from one source to another target.

A fourth method to train robots to adapt to dynamic and uncertain environments is meta learning (ML). ML is a paradigm that enables robots to learn how to learn, by improving their learning processes, algorithms, or parameters. ML can help robots to adapt quickly and efficiently to new tasks or domains, by learning from a variety of experiences, contexts, or objectives.

A fifth method to train robots to adapt to dynamic and uncertain environments is curriculum learning (CL). CL is a strategy that organizes the learning process of robots into a sequence of tasks or lessons, from easy to hard, from simple to complex, or from specific to general. CL can help robots to learn more effectively and efficiently, by providing them with appropriate challenges, feedback, and guidance, as well as by avoiding local optima, overfitting, or forgetting.

A sixth method to train robots to adapt to dynamic and uncertain environments is self-supervised learning (SSL). SSL is a technique that enables robots to learn from their own data, without requiring external labels or annotations. SSL algorithms allow robots to generate their own supervision signals, by exploiting the structure, regularity, or causality of their data or environment.

Resource optimization and management is as important to collective problem solving as it is to any existing system. Robots can optimize their collective performance by efficiently allocating resources among group members. Task scheduling, load balancing, and resource sharing strategies can improve overall system performance and longevity. Even though groups of robots are not as sensitive to the failure of an individual robot, the distribution of the load is important to ensure longer uninterrupted operation of each element.

Integration of heterogeneous capabilities is one of the properties of a group of robots consisting of robots of different types with various capabilities (for example, air, ground, water). Collective problem solving involves the synergistic integration of these capabilities to overcome challenges that individual robots cannot handle alone. For example, aerial robots may conduct surveillance, while ground robots perform detailed inspections.

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Scalability and reliability are what give advantage to group management and group problem solving. Collective problem solving must be scalable to accommodate different team sizes and adapt to failures or changes in the composition of the robot group. Robust coordination mechanisms ensure that the system remains effective even in the presence of communication delays, robot malfunctions, or environmental disturbances.

Conclusion

Collectively, a team of robots that collectively solve problems is transforming today's industries by creating more efficient, flexible and adaptive automation solutions. As industries continue to embrace robotics and artificial intelligence, the ability of robotic teams to collaborate will play a key role in shaping the future of manufacturing, logistics and other industries. Collective problem solving by a group of robots uses the principles of cooperation, coordination, and adaptation to solve complex tasks efficiently and effectively. This approach holds promise for a wide range of applications, including disaster response, environmental monitoring, infrastructure inspection, and autonomous logistics. An important aspect is understanding exactly how to achieve a system of groups of robots that will navigate unfamiliar terrain, make decisions based on received data, and quickly execute actions in order to achieve the ultimate goal.

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