Robotic Autonomy: A Survey

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Abstract

Robotic autonomy is key to the expansion of robotic applications. The paper reviews the success of robotic autonomy in industrial applications, as well as the requirements and challenges on expanding robotic autonomy to in needing applications, such as education, medical service, home service, etc. Through the discussions, the paper draws the conclusion that robotic intelligence is the bottleneck for the broad application of robotic technology.

Index Terms

Robotic Autonomy, Robot Intelligence, Industrial Robot

I. Introduction

Recently, robotic technology made impressive progresses and attracted more and more attentions. Despite the quick expanding of the research community, the application of robots are limited, partially because of lack of autonomy in real world settings.

Before we discuss the reasons for limited autonomy and challenges of improving autonomy in real world settings, let's first introduce levels of autonomy.

The levels of autonomy ranges from from no autonomy to fully autonomy.Depend on the applications, the autonomy could be separated into 4, 5, 6 or other numbers of levels. Based on the focuses of this work, we adopted the 5 levels autonomy definition.

1) Level 0: No Autonomy: Devices or equipment can be fully controlled by human and have no autonomy, regardless of the complexity or being powered/powerless. Such systems are still very useful and extend human's capabilities, but they solely rely on human's operation.

2) Level 1: No-adaptive Autonomy: With sensors, the loop of control of devices and equipment can be closed in order to automatic control the (often internal) status. Such systems are often simple and have no intelligence, but can outperform human's operations on speed, precision, and reliability. However, human's operations are still needed, but at a slightly higher level of control.

3) Level 2: Adaptive Autonomy: With intelligent systems or algorithms, the loop of control of devices and equipment can include external status, such as environmental changes or application changes. The closed loop thus can adapt to various environments, conditions, and requirements, can greatly reduce the need for human controls.

4) Level 3: Supervised Autonomy: When intelligent systems and the sensory systems are capable of processing rare conditions, rare needs, or high level tasks, these autonomous systems only rely on human's high level commands or rely on human operations at emergency.

5) Level 4: Full Autonomy: With full autonomy, robots have the human level intelligence, and can not only perceive and predict, but also are capable of deductive and inductive inferences. With this level of autonomy, human operations are no longer needed.

Up until today, we still lack of technology and materials for full autonomy, and robots are often used in applications with fixed requirements and environments, such as industrial assembly and packaging. The work reviews the recent progresses and discusses the focuses of the research community and remaining challenges, in the hope of inspire solving robotic problems.

II. Types of Mobile Robots

A. Ground Robots

There are many types of ground robots, including wheeled robots, tracked robots, legged robots and legless/snake shaped robots [1–12]. These ground robots have their unique challenges toward autonomy, such as kinematic control and dynamic control, and also share common research problems, such as environmental perception and path planning [13–16].

One of the most researched ground robots are autonomous vehicles. In the past two decades, autonomous cars made impressive success in business. Many companies, such as Waymo, Uber and Tesla, quickly expand and became giants and almost all traditional car makers, such as Toyata, Audi, Ford, BMW, quickly follow the path and compete the market. Although recent progress in Deep Learning injected energy to the autonomous vehicle industry, the real improvements in autonomy is much behind the projections from the companies. Especially in 2021, many of these companies tuned down their advertisement on autonomy after tremendous resources and efforts toward developing real self-driving vehicles.

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B. Airborne Robots

Airborne robots also have many types, such as single rotor robots, multi-rotor robots, fixed wing robots and bio-inspired flying robots[17–20]. Depend on the types of flying mechanisms, the difficulties of closed loop motion of control are drastically different. On top of the motion control, these robots often have lower difficulties on environmental perception and path planing as they often work in less crowded environments, comparing with ground robots. However, achieving the autonomy is still challenging because the airborne robots are often designed for complex tasks such as surveillance and object tracking, and their capabilities are beyond obstacle avoidance.

C. Water Robots

Water robots include both robotic boats and underwater robots. Between the two, the underwater robots attracted more attentions as they have broader military and commercial applications [21, 22].

III. Types of Manipulator Robots

A. Industrial Robots

Industrial manipulators demonstrated that robots can fundamentally changed the ways for manufacturing [23, 24]. Typical industrial manipulators are widely used in welding, painting, assembly, disassembly, packing and packaging, inspection and labeling. In these applications, the manipulators, the manufacturing processes, and the working environments are fully optimized, and environmental adaptiveness and robotic intelligence are not needed [25–27].

B. Cobot

Cobots, collaborative robots, are robotic manipulators that designed for human-robot interaction. Cobots work in close proximity with human, and can work in parallel or sequential with human. Cobots meant to broaden the applicability of robotic systems by avoiding explicitly design the manufacturing processs to exclude human works [28–32]. Existing cobots haven't been able to be widely applied to industry yet.

C. Medical Robots

Medical robots, especially surgical robots, became one of the successful applications in robotic technology. Various surgical robots have demonstrated the improved operational precision, the improved dexterity, the improved visualization, and the improved efficiency. However, autonomy for surgical robots are not fully exploited due to the requirements on environmental adaptiveness, domain knowledge and the liability associated with surgeries [33–35].

IV. Challenge in Robotic Autonomy

A. Robotic System Reliability

Robotics systems have many components, and a single problem in any of these components can jeopardize the performance and the stability of robots[36, 37]. Improving the stability and the performance of robotic systems requires the development of robotic technology and the accumulation of experiences[38]. Moreover, improving system reliability often relies on extra hardware and software[39, 40], which further improve the complexity of robotic systems[41].

Robotic systems continuously work in dynamic real environments[42–44], which has various adverse factors that cause a robotic system failure[45]. Because of the system complexity, the environmental complexity, and the task complexity, it is extremely challenging to maintain robots' performance and stability in real-world applications, under today's technology, regardless of the improvement of robotic technology and researchers' efforts. Experts' supervision on robotic systems can serve as guardians to robotic systems and allows introducing robotic systems into real-world applications.

B. Robotic Intelligence

Most of the existing robotic research focuses on robotic technology[46, 47]. However, domain knowledge is needed in many real-world applications[48–54]. Expert level knowledge is essential to successful robotic applications but is difficult to achieve[55–60]. Classical expert systems utilize rule-based intelligent systems and facing the exponential complexity increases[61, 62], thus are not easy to develop and maintain for complex applications[63, 64]. Recently, deep learning based methods achieved impressive progress and outperform human performance in many applications[65–68], such as natural language processing. However, deep learning methods often require a large amount of training data[69], which is often not available for robotic applications. Moreover, deep learning methods are often applied to address single-task problems and are sensitive to the change of data distributions. As a result, equipping robots with expert level skills is still a challenging and unsolved problem. Because of these limitations, supervised autonomy plays a significant role in accelerating introducing robots into real-world applications.

C. Robotic Collaboration

Collaboration is essential for complex tasks, even for a human being. Although there is a large amount of existing research and effort towards robot/human collaboration[70], existing results often aim to address single-task applications[71]. Therefore, utilizing human expert knowledge to decompose and simplify tasks into simpler tasks, which can be handled by robots, is important to extend robotic applications.

D. Ethical and Legal Vacancy

Although the study in robotics has made impressive progress in the past to centuries, and robots already started to address real-world problems, it is still blank in ethics and law for robots directly interacting with a human. For simple operations, such as driving, human beings can often reach a common consensus on the evaluation of the operations. For example, an operation causes a traffic accident and damage to human or properties are definitely failed. For complex operations, such as surgeries, even human experts can have conflict opinions toward some operations. This is often caused by the fact that the evaluation of the operation is complicated. as the results, the evaluations of hypothesizing operations are more complicated and often controversial. When the huge loss of values is associated with operations, human appeal lawsuit to seek for solutions. When such situation raised, a committee formed by human experts will be the reference for the court. For robots, when concerns are raised regarding the operations, human experts will evaluate the results. Clearly, supervised autonomy allows human experts to make critical decisions to ensure the robotic systems are safe and effective.

V. Toward Full Robotic Autonomy

A. Sensor Information

Sensors are fundamental and challenging components in robotic systems[72–76]. Even after decades of research, it is still difficult to increase robot perception to human level[77]. For example, tactile sensing is essential and fundamental to a human being but despite the impressive progress of force sensor matrix research, robot haptic sensing is far away from human performance[78], in both sensing precision and resolution[79, 80].

Another important problem is sensor fusion[81–83]. Human naturally uses all available information[84, 85], such as vision, hearing, and tactile, for performing tasks, but for robots, sensor fusion is still a challenging problem, especially with comparatively poor sensor information quality[86–88].

B. Robot Control

Robot control is a historical problem and remains challenging and attractive. There is a huge research community, which focuses on improving control efficiency[89] and system robustness[90, 91]. However, while modern robots often have redundancy for improved system reliability, it makes the control problem harder[92]. While multiple redundant robots work collaboratively, the control problem reaches a new level of complexity[93].

C. Robotic Intellgence

Human intelligence keeps increasing from new experiences and is superior in heuristic learning and reasoning[94, 95]. Robots need a similar learning capability to keep increasing performance. Robots also need to increase the reasoning capability to transform knowledge from domains to domains, which is a problem need to be addressed as soon as possible.

D. Robot/Human Interaction and Interface

Supervised autonomy needs robot-human interaction. The classical robot/human interaction has insufficient efficiency for supervised autonomy[96]. We need more than emergency stops to guide robots for improving robotic system performance[97].

VI. Conclusion

Robotic autonomy is key to broaden the application of robots. Through the discussion of existing robotic systems and their applications, it is clear that robotic autonomy still remains challenging in real world applications. Among all the challenges, robotic intelligence is one of the important one that limits the robots from moving toward full autonomy.

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