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From Unmanned Systems to Autonomous Intelligent Systems

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1. Introduction

Artificial intelligence (AI) is a rapidly growing field of technology, which "will enliven inert objects, much as electricity did more than a century ago. Everything that we formerly electrified will now cognitize" [1]. AI advances are constantly pushing the frontier of what machines can do. Increased attention is being placed on AI research, as well as its development and deployment by commercial investors, defense strategists, and policy makers [2]. On July 20, 2017, the Chinese government released a strategy for developing AI technologies, entitled "New-Generation Artificial Intelligence Development Plan," which sets out policy options and delineates the overarching goal of making China a world leader in AI by 2030.

2. A brief history of AI and related concepts

The beginnings of modern AI can be traced back to the classical philosophers' attempts to describe the process of human thinking as a symbolic system long ago. It is widely acknowledged that the field of AI as an independent academic discipline was not officially founded until the Dartmouth conference, held in the summer of 1956, when John McCarthy coined the term "artificial intelligence," to distinguish the field from cybernetics, which was a term coined by Norbert Wiener to refer to his vision of autonomous (unmanned) systems [3]. The goal of AI is to build systems that can learn and adapt as they make well-informed decisions, that is, systems that have certain levels of autonomy (i.e., the capability of task and motion planning) as well as intelligence (i.e., the capability of decision-making and reasoning). Although there have been fluctuations in the popularity of AI, the recent explosion of interest in AI started around 2006 [3]. It emerged because of the convergence of three enabling factors: ① the availability of large, unstructured datasets useful for training powerful machine learning and AI models; ② rapid software and hardware advances such as deep learning algorithms and graphics processing unit (GPU)-based computing platforms; and ③ the emergence of cloud business models. This explosion has advanced the state of weak AI, which refers to algorithms or computer software capable of addressing specific classes of problems, such as document classification, object detection, game playing, disease diagnosis, and autonomous navigation. However, many believe that all current AI systems (technologies) fit within in the category of weak AI, therefore falling short of strong AI [4].

There is no commonly accepted definition of AI, which is primarily due to the different approaches adopted for AI research by professionals across different fields. Existing definitions of AI can be roughly summarized in four groups (Table 1). These four definitions specify the four possible goals to pursue in the category of artificial general intelligence (AGI), which refers to systems capable of achieving human-level autonomy and intelligence across a wide variety of tasks.

3. Autonomous intelligent (unmanned) systems

An unmanned system is defined as an electro-mechanical system capable of exerting its power to perform designated missions with no human operator aboard [5]. Contemporary systems, such as multi-robotic systems, unmanned air, ground, and marine vehicles (UAVs, UGVs, and UMVs), mobile, edge, and cloud computing systems, and financial, manufacturing, and electricity systems, are increasingly characterized by their decentralization, ubiquity, and interconnection, that is, they are systems composed of autonomous entities. Because of the seamless integration and the dynamic nature of their physical components, cyber infrastructure, and social contexts, such engineered systems must operate with increasing levels of autonomy and intelligence to make decisions and manipulate their environment [6,7].

UAVs were originally used by the military in 1917 when the US Navy commissioned the design of the speed-scout for use against German Uboats, which suffered numerous failures before it achieved its first successful flight on March 6, 1918, marking the first flight of a UAV. Ever since then, unmanned systems have developed rapidly, which can be divided broadly into three stages: from programming-based to automatic unmanned systems, intelligent unmanned systems, and autonomous intelligent unmanned systems. The first stage is limited in the sense that the system can only work as programmed a priori, and cannot adapt to any

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Table 1
Taxonomy of historical AI definitions [4].

	Human-like	Rational
Thought	Systems that think like humans "The automation of activities that we associate with human thinking, activities such as decision making, problem solving, and learning."—Bellman, 1978.	Systems that think rationally "The study of computations that make possible to perceive, reason, and act."—Winston, 1992.
Action	Systems that act like humans "The art of creating machines that perform functions that require intelligence when performed by people."—Kurzweil, 1990.	Systems that act rationally "The branch of computer science that is concerned with the automation of intelligent behavior."—Luger and Stubblefield, 1993.

changes in the environment. The second stage is at an advanced level, in which the system has certain sensing, decision-making, and control capabilities and can adjust in accordance with the environmental variations. In the final stage, unmanned systems have high levels of autonomy and intelligence, matching or even surpassing the humans across many tasks.

The autonomous intelligent system (AIS) is an emerging interdisciplinary field that relies on big data and AI (among other scientific and technological advances) to create unmanned systems with integrated task and motion planning, as well as decision-making and reasoning capabilities. AIS can accomplish general-purpose tasks with no or limited direct human involvement, and it is made possible by the convergence of digital design (AI, big data, control, etc.), robotics, as well as the constructed environment [8]. Examples of AISs include autonomous driving cars, smart manufacturing robots, and social agents for companionship or comfort. Relative to common unmanned platforms that may be rule-based, or controlled remotely by humans or by other machines, AIS features several defining and unique characteristics: (increasing levels of) autonomy, intelligence, and cooperativity. First, AISs are assembled with autonomous components whose behavior(s) may be complex and volatile, in the sense that the components may become unavailable suddenly, break down completely, or change their behavior(s). The AISs are also intelligent enough, that is, capable of reasoning over a large body of knowledge and experiences, to detect said faulty behavior, adapt to perform appropriately in critical situations, and return to its original functioning by means of making well-informed decisions. Furthermore, when engaged in complicated and challenging tasks, AISs can seek to closely coordinate and cooperate with each other to develop high-level collective behavior. Hence, AIS is the ultimate goal of AI research, and AIS research provides a promising path to AGI.

4. Representative applications of AISs

AISs are rapidly finding applications in many diverse domains, ranging from commercial, industrial, and medical sectors to physical security, national defense, as well as space exploration. In 2016, the computer program AlphaGo, as part of Google DeepMind, defeated for the first time a human professional player in a game of Go [9], which has since inspired several major breakthroughs across a range of challenging science and engineering domains. We highlight some representative and contemporary examples of AISs below.

4.1. Autonomous driving

Autonomous driving (a.k.a., self-driving) is an extremely popular area of research that explores the roots of autonomy and intelligence of a self-driving vehicle. In the five years from 2016–2021, more than 43 000 conference papers and 8 000 journal (including magazine) articles were published by the Institute of Electrical and Electronics Engineers (IEEE) alone on the topic of autonomous driving. Self-driving cars are currently not perfect in their operation, as evidenced by the 2018 self-driving vehicle accident in Tempe, Arizona, USA, in which a pedestrian was killed by a sport-utility vehicle controlled by an autonomous algorithm while the safety driver was unable to prevent the crash. Also, as observed in Ref. [10], autonomous vehicle systems still far from human or animal's visual systems with respect to performance. Innovative solutions, such as bio-inspired visual sensing, multi-agent collaborative perception, and control capabilities that mimic the working principles of biological systems are needed [11]. It is predicted that by 2030, autonomous driving will become sufficiently reliable and safe to displace most human driving, after achieving higher-levels of robotic autonomy and vehicle intelligence [12].

4.2. Medicine and healthcare

The coronavirus disease 2019 (COVID-19) outbreak has become a global pandemic. At the time of writing, the total number of confirmed COVID-19 cases worldwide has topped 113 million. Unfortunately, this number is still growing at a rate of about 400 000 cases a day, according to the World Health Organization. Global effort is required to fight against COVID-19. AISs could be part of the solution, which show significant potential to be deployed for disinfection, diagnosis, monitoring, assisting in large-scale screening and surgery, delivering medications and vital supplies, as well as conducting rehabilitation training of the elderly for the aging society. As summarized in Ref. [13], robotic systems can support the healthcare system and defend the public health in at least four macro areas: clinical care (e.g., telepresence, telemedicine, and decontamination), logistics (e.g., handling, storage, and transportation of healthcare waste), reconnaissance (e.g., monitoring and managing compliance with voluntary quarantines), and maintenance (e.g., enhancing the continuity of work and socioeconomic functions during quarantines). It has also been noted that many of these uses are already being actively explored in China, albeit currently only in limited regions, with a majority of these applications serving only as proofs of concept. Each of these application areas of robotics calls for more research. Future opportunities lie in developing medical AISs capable of triaging, evaluating, monitoring, treating, as well as providing companionship and comfort for patients from a safe distance.

4.3. National security and defense

In addition to their widespread civil applications, AIS technologies have already diffused into military operations [14]. As early as 2003, the US Army launched jointly with the Defense Advanced Research Projects Agency (DARPA), the Future Combat Systems program, which was the largest and most ambitious planned acquisition program in the US Army's history [15]. The goal was to design an entire brigade equipped with hundreds of manned and unmanned vehicles that were connected with a super-fast and flexible battlefield network and thus capable of achieving unprecedented levels of interoperability and tactical coordination. In 2004, Defense Research and Development Canada initiated the AIS program, publishing its strategic plan to increase the autonomy and intelligence of military vehicles and systems [16]. Key challenges targeted include the capabilities of these AISs to perform complex tasks through the comprehension of their unstructured environments with minimal human involvement, as well as the ability to learn, adapt, and exchange information between autonomous entities, and to achieve collective intelligence and enhanced system effectiveness. More recently, DARPA's Collaborative Operations in Denied Environment (CODE) program also seeks to expand the mission capabilities of UAVs via increased autonomy as well as inter-platform collaboration [17]. The US military is already integrating AISs into combat through the Project Maven initiative, which has exploited (and demonstrated the power of) AI algorithms to identify targets of interest in Iraq and Syria [4].

4.4. Deep space exploration

As part of the Chinese Lunar Exploration Program, China's Chang'e 5 successfully accomplished its mission of bringing samples from the moon back to Earth on December 17, 2020, for the first time such samples had been collected in almost 50 years. Two samples were collected: one from the surface of the moon and the other from approximately two meters underground. Both were loaded into a lunar ascent vehicle, which then took off to link up with the mission's orbiter (i.e., the Earth return vehicle). This union was recognized to be the first time that two robotic spacecraft accomplished a fully autonomous docking beyond Earth orbit. Similarly, National Aeronautics and Space Administration (NASA)'s Perseverance rover, praised as the most technologically advanced robotic system geologist ever made, landed itself safely and flawlessly on Mars on February 18, 2021, which was possible thanks to its advanced landing system that can quickly, accurately, and autonomously comprehend the local environments and adjust its trajectory during its entry, descent, and landing (EDL) phases (a.k.a., the "seven minutes of terror"). The "vision for space exploration" of the solar system and even places beyond necessitate even higher requirements for collaborative autonomy and spacecraft intelligence to equip future deep space explorers with the ability to detect and respond to unexpected conditions, to recognize and characterize unforeseen features of interest, and to interpret data content and rewrite and modify observation plans [18].

5. Outlook

Despite these exciting progress and successful applications, many fundamental challenges remain for AIS research, and chief among them are the challenges of full autonomy and robotic general intelligence. So far, current AIS research and effort have mostly been focused on individual robotic systems (i.e., a single agent), whereas less has been studied and understood regarding robotic swarms, and even less about groups of robots (e.g., swarms of heterogenous agents or multilayer systems [19]); see Fig. 1 for an illustration. On these bases, future developments and opportunities lie in exploring the roots of autonomy and intelligence across the three levels of AISs. We outline in the following some of the key challenges that are most prominent in our endeavor to fulfill the vision of AISs, particularly those which may lead to significant scientific advances in the next decade.

For an intelligent agent (e.g., an artificial embodied system or a robot mind), the fundamental topics to be investigated include [20] understanding what kind of intrinsic developmental program governs the developments of the agent's cognitive capabilities (e.g., vision, audition, traction, language, planning, decision-making, and action execution) during autonomous repeated interactions with unstructured environments when it uses its sensors and effectors, and how does this process operate? A more technologically relevant and pragmatic question is how to create an AIS that can develop the complex, multifaceted, and highly integrated capabilities of an adult brain? The idea of cognitive (or mental) development has long been explored by psychologists and neuroscientists, yet it has not gained much attention in the AI and robotics community. Computational and data-driven (i.e., machine-learning) studies of autonomous mental development may be a promising solution for understanding natural intelligence and constructing intelligent machines.

Since the 1990s, substantial progress has been made in several areas of artificial swarm intelligence, including understanding the influences of variability between individuals and adaptivity of those individuals' characteristics on the cluster's collective behavior. Research has also been conducted on establishing the basic theories of controllability, observability, as well as evaluating the stability of synchronization algorithms for homogeneous agents in structured and laboratory environments. Nonetheless, there is a basic need for understanding how and when clusters of synchronization emerge, merge, and persist in unstructured and dynamic real-world environments [21]. Moreover, characterizing how an individual in a cluster (i.e., swarm) acquires a specific collective behavior while balancing the development of individualistic behavior constitutes another key challenge [22]. Additionally, what are the control principles of complex robotic swarms? These control principles hold the key to understanding collective behavior, synchronization principles, as well as the failure mechanisms of complex and large-scale networks.

Ultimately, most of the functionalities of AISs can be distilled to managing limited, changeable, and shareable public resources, such as transportation and storage capacities, energy, and services, to accomplish challenging (super) human-level tasks. According to the "tragedy of the commons" philosophy, misalignments between individuals' selfish interests and the group's interests can lead to the overexploitation and potential collapse of public resources (or the entire production system), whereas cooperative relationships between individuals in a cluster, as well as between swarms in a larger system (group), can increase those same public resources [23]. Therefore, there is an emergent demand to decipher

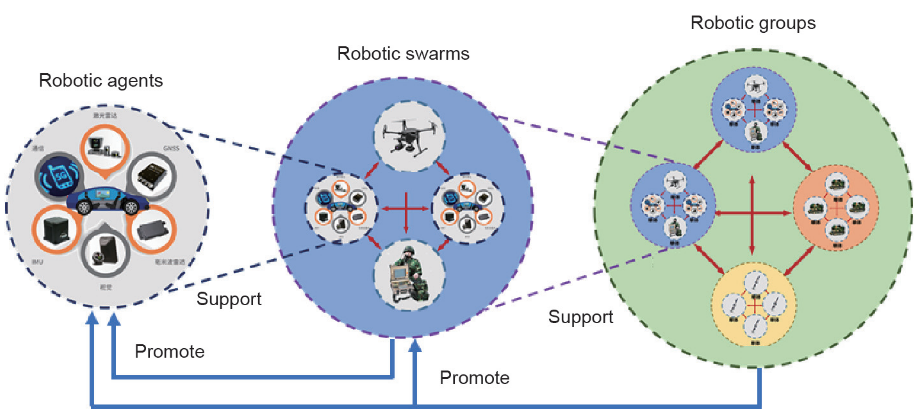

Fig. 1. Future research developments for AISs.

the intricate interactions between the collective behaviors of clusters, to establish a foundational control theory (one that includes controllability, observability, and control principles) for groups of heterogenous AISs, as well as to explore the evolutionary mechanisms underlying cooperation in stochastic games between swarms to optimally and sustainably exploit public resources.

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