Between the Megalopolis and the Deep Blue Sky: Challenges of Transport with UAVs in Future Smart Cities

Blue Sky Ideas Track

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ABSTRACT

With the rapid increase of the world's urban population, the infrastructure of the constantly expanding metropolitan areas is undergoing an immense pressure. To meet the growing demands of sustainable urban environments and improve the quality of life for citizens, municipalities will increasingly rely on novel transport solutions. In particular, Unmanned Aerial Vehicles (UAVs) are expected to have a crucial role in the future smart cities thanks to their interesting features such as autonomy, flexibility, mobility, adaptive altitude, and small dimensions. However, densely populated megalopolises of the future are administrated by several municipals, governmental and civil society actors, where vivid economic activities involving a multitude of individual stakeholders take place. In such megalopolises, the use of agents for UAVs is gaining more interest especially in complex application scenarios where coordination and cooperation are necessary. This paper sketches a visionary view of the UAVs' role in the transport domain of future smart cities. Additionally, four challenging research directions are highlighted including problems related to autonomy, explainability, security and validation & verification of the UAVs behavior.

KEYWORDS

Multiagent Systems; Unmanned Aerial Vehicles; Intelligent Transport Systems; Smart Cities

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1 INTRODUCTION

Since the early days of the industrial revolution, people started migrating to cities in droves. In 2007, the percentage of urban population exceeded that of rural population for the first time in history [37]. According to the UN, this *Urbanization* is expected to accelerate raising the percentage of people living in cities and metropolitan areas to 68% of the world population by 2050 [36]. The result is a denser city infrastructure – where the city is actually the backdrop for all of the social, economic and commercial activities. To accommodate this evolution, cities need to rely on technologies to help them improve the quality of life of their citizens.

Unmanned Aerial Vehicles (UAVs), colloquially known as drones, are becoming increasingly popular for civil applications in several domains such as transport, energy, telecommunication, environment preservation and infrastructure. According to Teal Group's 2018 World Civil UAV Market Profile and Forecast report [35], civil UAV production will total US$88.3 billions in the next decade, with a 12.9% compound annual growth rate. The key features making UAVs interesting to use are their small dimensions, effortless deployment, good maneuverability, simple mechanics and adaptive altitude.These features make UAVs accessible for civil applications deployed in urban environment as a practical solution

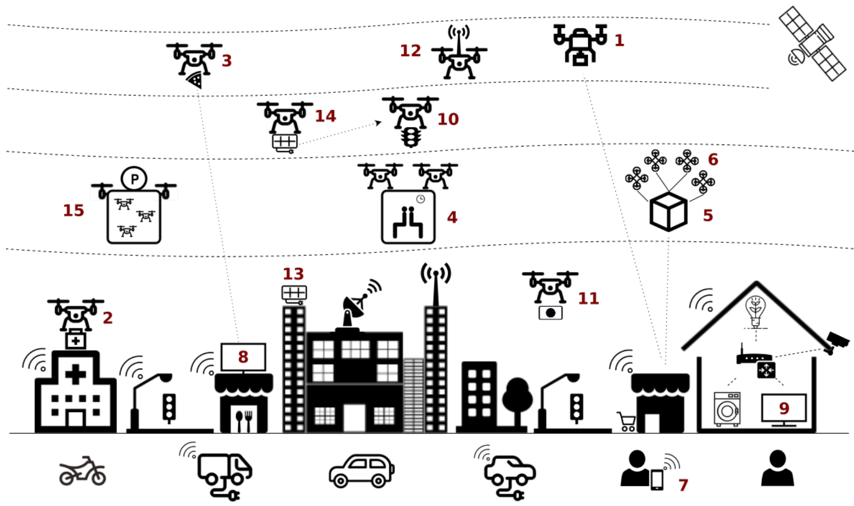

Figure 1: UAVs in a future smart city.

for cost-efficient and rapid delivery. One of the best-known examples is Amazon Prime Air where UAVs are used to deliver packages to customers [6, 13].

Despite these initial successes, UAV technology is still in its early stages of development. For this reason, considerable limitations should be addressed before a large scale deployment of UAVs is possible. The main drawbacks to mention are related to the safety of humans and the integrity of goods with UAV failures [41], and the high amount of energy consumed by UAVs coupled with their limited battery life [31]. Moreover, since civil applications are mostly deployed in urban environments involving multi-actors, considerable research efforts should be dedicated to enhancing the UAV perceptual and cognitive intelligence required to coordinate complex environments [17].

In multi-actor environments such as megalopolis, we envision a huge number of actors with a high density within the environment. Considering that a part of these actors will interact with intelligent, autonomous and connected objects, or will be one of them, *e.g.* UAVs, it will be impossible to have a human associated to each of these objects, *e.g.* as a pilot. This implies a need of autonomy for these objects, cooperation among them for reaching their goals and negotiation between them to avoid conflicts. The agent paradigm is well suitable for modeling, implementing and deploying autonomous entities into multi-actor environments [18]. Therefore, agents play a significant role in the coordination, cooperation, competition and negotiation between all actors, *e.g.* the study of the swarms' formation of multiple UAVs [10, 32].

While other work [24, 26] considered the challenges of deploying UAVs in smart cities, they mainly mentioned the existing research with no focus on the role of agents. Consequently, the vision exposed in this paper focuses on the application of multiagent concepts to smart cities, and specifically to UAVs in these cities. Several research directions related to multiagent systems in this context are proposed.

The rest of this paper is organized as follows: Section 2 states the future vision of intelligent aerial systems in smart cities. Section 3 identifies the major challenging research directions. Section 4 concludes this paper.

2 FUTURE AERIAL TRANSPORT SYSTEMS IN SMART CITIES

Today, the need for transport of people and goods is increasing but so is traffic congestion, air pollution, road accidents and climate change. Some of the solutions for these problems come in a form of ride-sharing [2, 33]. However, in the future, cities will need to rely on "high-tech" mobility solutions including Internet of Things (IoT) and UAV technologies. Thanks to their autonomy, flexibility, mobility, low-cost maintenance and coverage, UAVs are a useful solution for many of the transport challenges. Below are listed our key visions of the future of transport with UAVs in smart cities.

In-the-Air Services: Recent applications of UAVs concern the fast delivery of goods, such as commercial products ((1) in Figure 1), medical products or first aid kit (2) or food (3). In the future, other entities may be carried by UAVs, such as passengers (4) and big/heavy containers (5). These entities could be carried by a single UAV, or by a swarm of UAVs (6).

Smart transport and Traffic Management: Another vital contribution of UAVs is smart transport, which will likely be another key area of development for any future smart city. Basically, every city can rely on UAVs for improving urban transport and creating a sustainable ecosystem. For example, a flying UAV can guide pedestrians on the ground via smart devices (7) or information panels (8), or guide other UAVs in the air through Vehicular Ad-hoc Networks (10). The latter are known as smart traffic management UAVs that control the flow of people and goods in the sky. Air traffic management will divide the sky into free flying areas and corridors in which all the UAVs will fly in the same direction. For example, heavy lifting (5) and passengers transport (4) can occupy the lowest corridor.

Air and Climate Management: As cities inevitably become busier, the quality of the air, climate and noise levels created by city systems can be monitored (11) and citizens can be informed (8 or 9). Municipalities can act with real-time actions to better manage the comfort and health of the citizens. To build the transport infrastructure of the future in a more sustainable way, zero-emission and low-noise electric power is the solution. Using electric vehicles like UAVs tends to provide a silent, clean, emission-free and resource efficient city minimizing the risks affecting the health and safety of citizens. Furthermore, UAVs can be equipped with sensors. Data gathered from these sensors can be used by stakeholders to build a map of the environment state, such as air pollution and noise. Yet, a huge number of flying UAVs in the sky raise some environmental issues such as the recycling of out-of-service UAVs and the supply of clean and renewable energy to charge them.

In-the-Air Infrastructures: Connecting objects within the smart cities via wireless technologies is already a reality (*e.g.* WiFi, 4G/5G, satellite, etc.). UAVs can offer a novel communication infrastructure by providing communication nodes where static/conventional nodes cannot be present (12). Because of the UAV mobility, this infrastructure may be deployed dynamically, even when the ground communication infrastructure cannot be used, *e.g.* in case of natural disaster (see below). Another example is when the population density increases at a specific location for a limited time, *e.g.* at football stadium. In this case, UAVs can offer an efficient networking service to the spectators. Energy consumption of UAVs is an issue: the average flying time for civil multirotor UAVs is around 20 minutes [23]. Consequently, it is mandatory to provide energy charging services to the UAVs on the buildings (13). This service may be also provided on-the-fly by other UAVs with eco-friendly solar power systems (14). Other types of infrastructures may appear in future smart cities, such as aerial parking areas (15) in which the UAVs may park and/or charge their batteries.

Crowd Management: Safety and security are major concerns for every smart city and they will be even more critical in future megalopolises. Already today, UAVs are playing a huge role in crowd management [1, 34, 42], and could definitely improve this field in the future. For example, police and municipal agencies can use UAVs to keep an eye on the crowd during any event (11). This will result in safer cities to live in as well, but will raise privacy issues.

Natural Disaster Control and Emergency Response: In case of disasters in the megalopolis, UAVs can be used to minimize the response time and losses. Floods, fires and earthquakes are some of the best examples in which authorities can take precautionary measures by monitoring (11) and deploying medical teams (2) or by providing communication infrastructure (12). UAVs can here analyze the entire situation and help with a quicker response than emergency calls.

3 CHALLENGES AND RESEARCH DIRECTIONS FOR AGENTS

The following list provides a synthesis of the major challenges and research directions related to UAVs for agents.

3.1 Making the UAV autonomous

References cite automated decision aiding/decision making in mission management as one of the most difficult problems leading to autonomy. Mission management includes other difficult issues like communications, task and path planning/re-planning, and man-machine interface. The challenge is to optimally update the off-line plan as per the new received information and/or the unforeseen occurred events. The optimization problem is dominated by size, complexity, uncertainty, and the fact that the mission could be shared by different UAVs. This leads to problems related to the cooperation and coordination of the autonomous UAVs, and opens the door for challenges like flexible autonomy [11] and initiative decision-making [14]. Cognitive architectures (*e.g.* SOAR [21]) and Belief-Desire-Intention (BDI) agent architecture [8] are increasingly becoming used to equip the UAVs with greater autonomy. With these proactive agents representing the UAVs, the latter are capable of autonomously managing their actions and behavior to reach their goals [4, 29].

3.2 Explaining the UAV Behavior

The confirmed tendency towards the development of increasingly autonomous UAVs, would minimize the human intervention by relieving the human operator from the burden of continuously monitoring the UAVs. Nevertheless, in unpredictable situations, the UAV behavior might not conform to the expectations of the human operator. For instance, in a product delivery scenario, an autonomous UAV may choose to deviate from its expected path because of an unforeseen event. The downside of this autonomous, complex and unforeseeable behavior is that it may become non-understandable for the human operator which would have a negative impact on the trust between the UAV and the operator. Moreover, as shown by recent user studies, this problem is aggravated by the fact that remote robots (including UAVs) tend to instill less trust than those co-located [5, 19]. Therefore, enhancing the UAVs with explaining capabilities would allow the human operator to understand the reasons behind their behavior and raises the trust in autonomous UAV systems. Furthermore, explainability may go beyond human-agent relations to agent-agent relations. Hence, to achieve a smooth collaboration among heterogeneous UAVs, they should explain their behavior to each other in order to reach mutual understanding [12].

Recent developments of the eXplainable AI (XAI) domain [3] help UAVs to move in this direction, and there exist common points allowing for synergies between the two domains. One key point is agent architecture. Examining recent multi-agent UAV research works shows that many of these works rely on BDI agent architecture [15, 40]. As shown by recent studies, using BDI agents is a promising approach to develop explainable agents [9]. A key explanation for this promising success lies in the fact that BDI paradigm is inspired from *folk psychology* [20, 22] which means that "*the core concepts of the agent framework map easily to the language people use to describe their reasoning and actions in everyday conversations*" [28]. Therefore, BDI architecture offers a more straightforward description making models easier to explain for end-users. For this reason, UAV agents with BDI architectures are likely to increase in numbers if the explainable UAV behavior is to become a hot research topic.

3.3 Ensuring Security and Authentication

The quest of developing autonomous and decentralized UAV systems raises several challenges related to security and authentication. For instance, within a swarm, a UAV must be able to detect and entrust its peers, and ensure data confidentiality and integrity. Otherwise, faulty or malicious UAVs may deviate the swarm behavior [16]. These challenges are accentuated by the fact that most UAV swarms are designed to operate autonomously without a central regulating authority. Recent research has outlined *Block-Chain Technology* (BCT) as a potential solution to overcome this problem. In addition to providing a platform allowing for secured interactions among UAVs, BCT can also be used to enhance the decentralized decision making of the UAV swarm [7] since it allows all the participants to share an identical view of the world, and facilitate agreements among UAV teams [16]. Yet, before BCT is ready to be used with UAVs, several limitations must be solved [16]: (i) *latency*: the time required to update the block-chain is too long to allow real-time compliance (a common requirement in UAV applications); (ii) Most of the UAVs are resource-constrained devices which might be unable to undertake the heavy computations demanded by BCT; (iii) On the long run, BCT can be very demanding in terms of bandwidth and communication overhead since all agents should share a copy of a long "ledger" of interactions [39]. This issue, known as "bloat", poses a considerable challenge to UAV teams which have limited hardware and communication capabilities.

3.4 Verifying and Validating the UAVs Behavior

The more complex a UAV software function gets, the more difficult it becomes to test [38]. Furthermore, functional requirements are only one aspect of a system. Beyond the pure verification of a requirement lies the benchmark of the implemented solution. The resulting outcome may be determined by a test of the requirement, but the specific path to the solution can have different levels of quality. Therefore, additional tests must verify that the specified safety boundaries, as well as additional constraints, are met by the proposed solution. To be able to assess highly automated functions and to be able to assure a high-quality software system, it is, therefore, necessary to implement a scoring system or a benchmark to evaluate the autonomy using non-functional requirements. For example, for path planning the standardized benchmark by [25] is utilized to measure the correctness and result quality by expressing a set of pass/fail criteria from the standardized baseline solution.

Note that benchmarks are problem specific, and not implementation specific. This enables developers not only to test a path-planning algorithm automatically, without a manual review from an engineer, but also to evaluate algorithms and compare them with different implementations and solution approaches. The development of such automatic benchmarks for additional problems like sensor fusion and computer vision, to generally assess the capability to fulfill navigation safety and performance requirements, will be critical to the progress of UAVs and the evaluation of new approaches [38].

The growing pressure to innovate and the demand for shorter development cycles require changes in the UAV development methodology. As a result, there is a shift in the demands on testbed systems. This desire for shorter development times stands opposed to the growing complexity required for developing of increasingly automated and autonomous systems [30]. Enabling early validation of such system designs requires the simulation of components [27]. This requires the development of adapted simulation environments, possibly real-time, composed of a collection of reusable modules combining real and virtual components (also called XiL: X-in-the-Loop, where X meaning alternatively Model, Software, Hardware or Human).

4 CONCLUSION

Nowadays, urban population is witnessing an unprecedented sharp increase, as cities are the centers of education, innovation, culture and opportunities. In the coming decades, the flourishing of megalopolises is inevitable, and smart measures should be taken to guarantee a good quality-of-life for their dwellers. The aim of this paper is twofold. First, list and discuss our key visions of the aerial UAV transport in future smart cities. Second, outline the key challenges and research directions for agents as follows: (i) Design of fully autonomous UAVs; (ii) Explanation of the UAVs behavior when they are part of a complex system; (iii) Security and authentication of UAVs; (iv) Verifying and validating the UAVs behavior.

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