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RESEARCH PAPER ON DRONE BALANCING AND COLLISION AVOIDING

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ABSTRACT

With the rise of Deep Learning approaches in computer vision applications, significant strides have been made towards vehicular autonomy. Research activity in autonomous drone navigation has increased rapidly in the past five years, and drones are moving fast towards the ultimate goal of near-complete autonomy. However, while much work in the area focuses on specific tasks in drone navigation, the contribution to the overall goal of autonomy is often not assessed, and a comprehensive overview is needed. In this work, a taxonomy of drone navigation autonomy is established by mapping the definitions of vehicular autonomy levels, as defined by the Society of Automotive Engineers, to specific drone tasks in order to create a clear definition of autonomy when applied to drones. A top–down examination of research work in the area is conducted, focusing ondrone navigation tasks, in order to understand the extent of research activity in each area. Autonomy levels are cross-checked against the drone navigation tasks addressed in each work to provide a framework for understanding the trajectory of current research. This work serves as a guide to research in drone autonomy with a particular focus on Deep Learning-based solutions, indicating key works and areas of opportunity for development of this area in the future.

1. INTRODUCTION

As small form factor UAVs similar to the drone pictured in Figure 1 flooded the market, several industries adopted these devices for use in areas including but not limited to cable inspection, product monitoring, civil planning, agriculture and public safety. In research, this technology has been used mostly in areas related to data gathering and analysis to support these applications. However, direct development of navigation systems to provide great automation of drone operation has become a realistic aim, given the increasing capability of Deep Neural Networks (DNN) in computer vision, and its application to the related application area, vehicular autonomy. The work outlined in this paper is twofold:

(1) It provides a common vocabulary around levels of drone autonomy, mapped against drone functionality.

(2) It examines research works within these functionality areas, so as to provide an indexed top–down perspective of research activity in the autonomous drone navigation sector. With recent advances in hardware and software capability, Deep Learning has become very versatile and there is no shortage of papers involving its application to drone autonomy. While domain-knowledge engineered solutions exist that utilize precision GPS, lidar, image processing and/or computer vision to form a system for autonomous navigation, these solutions are not robust, have a high cost for implementation, and can require important subsystems to be present for optimal operation, such as network access. The focus in this paper is on navigation works that utilize Deep Learning or similar learning-based solutions as a basis for implementation of navigation tasks towards drone autonomy. Just as Deep Learning underpins the realization of self-driving cars, the ability of trained Deep Learning models to provide robust interpretation of visual and other sensor data in drones is critical to the ability of drones to reach fully autonomous navigation. This paper aims to highlight navigation functionality of research works in the autonomous drone navigation area, across the areas of environmental awareness, basic navigation and expanded navigation capabilities. While the general focus is on DNN-based papers, some non-DNN-based solutions are present in the collected papers for contrast.

2. METHODOLOGY

As a first step, we need to define the concept of autonomy for drones, with a view to recognising different levels of autonomous navigation. This paper identifies the emergent navigation features in current research against these levels. We apply the Six levels of autonomy standard published by the Society of Automation Engineers (SAE) International. Though the context of these levels was intended by SAE for autonomous ground vehicles,the logic can apply to any vehicle capable of autonomy. The concept of autonomy for cars and drones is similar, implying a gradual removal of driver roles in the navigation of obstacles and path finding. This, progressing to fully independent autonomous navigation regardless of restrictions due to surface bound movement or obstacles. By examining the SAE levels of autonomy for cars, we note how each level is directly applicable to drones. This provides a useful line of analysis for our overview In Figure 2, we set out the functionality of drone navigation, mapped against these levels of autonomy. Autonomy starts at Level 1 with some features assisted, including GPS guidance, airspace detection and landing zone evaluation. These features are designed to provide automated support to a human operator. These features are already to be found in commercially available drones. Level 2 autonomous features are navigational operations that are specific and use case dependent, where an operator must monitor but not continuously control. In the context of drone operation this can include features where the drone is directed to navigate autonomously if possible, e.g., the "follow me" and "track target" navigational commands. Some of these features are available in premium commercial products. Level 3 features allow for autonomous navigation in certain identified environments where the pilot is prompted for engagement when needed. At level 4 the drone must navigate autonomously within most use cases without the need for human interaction. Level 5 autonomy implies Level 4 autonomy but in all possible use cases, environments and conditions and as such is considered a theoretical ideal that is outside the scope of this overview. Though this paper aims at evaluating the features of papers in the context of Level 4 autonomy, it was found that the bulk of the papers approached in the research pool involved Level 2 or 3 autonomy, with the most common project archetype involving DNN training for autonomous navigation in a specific environment.

a. Areas Of Work

This encompasses any feature that is included in the referred solution as analysis of the drone's spatial environment; though basic navigation features can be developed without this understanding, it limits the capability of the said navigation. Projects that do not include awareness features could lead to limited command capability and an over-reliance on prediction; the feature mappings of the awareness section can be seen in Table 1.

Spatial Evaluation (SE): The drone can account for the basic spatial limitations of its surrounding environment, such as walls or ceilings, allowing it to safely operate within an enclosed space.

Obstacle Detection (ODe): The drone can determine independent objects, such asobstacles beyond the bounds of the previously addressed Spatial Evaluation, but does not make a distinction between those objects.

Obstacle Distinction (ODi): The drone can identify distinct objects with independent properties or labels, e.g., identifying a target object and treating it differently from other objects or walls/floors in the environment.

Autonomous Movement (AM): The drone has a navigation policy that allows it to fly without direct control from an operator; this policy can be represented in forms as simple as navigation commands such as "go forward" or as complex as a vector of steering angle and velocity in two dimensions that lie on the x–z plane.

Collision Avoidance (CA): The drone's navigation policy includes learned or sensedlogic to assist in avoiding collision with non-distinct obstacles.

Auto Take-off/Landing (ATL): The drone is able to enact self-land and take-off rou- tines based on information from its awareness of the environment; this includes determining a safe spot to land and a safe thrust vector to take off from.

3. MODELING AND ANALYSIS

We identified that autonomous navigation features fall into three distinct groups: "Awareness", which details the vehicle's understanding of its surroundings, which can be collected via non-specific sensors; "Basic Navigation", which includes the functionality expected from autonomous navigation, such as avoiding relevant obstacles and collision avoidance strategies; and "Expanded Navigation", which covers features with a higher development depth such as pathway planning and multiple use case autonomous navigation. These groupings and their more detailed functional features are listed in Figure 3, as identified for Level 4 automation. In addition, we note that common engineering features are a useful category for this overview of navigation capability, and we include these as a fourth category for analysis. This is done to acknowledge projects in the research pool that are aimed at achieving a goal within a given hardware limitation, such as optimizations for lower-end hardware and independence from subsystems such as wireless networks.

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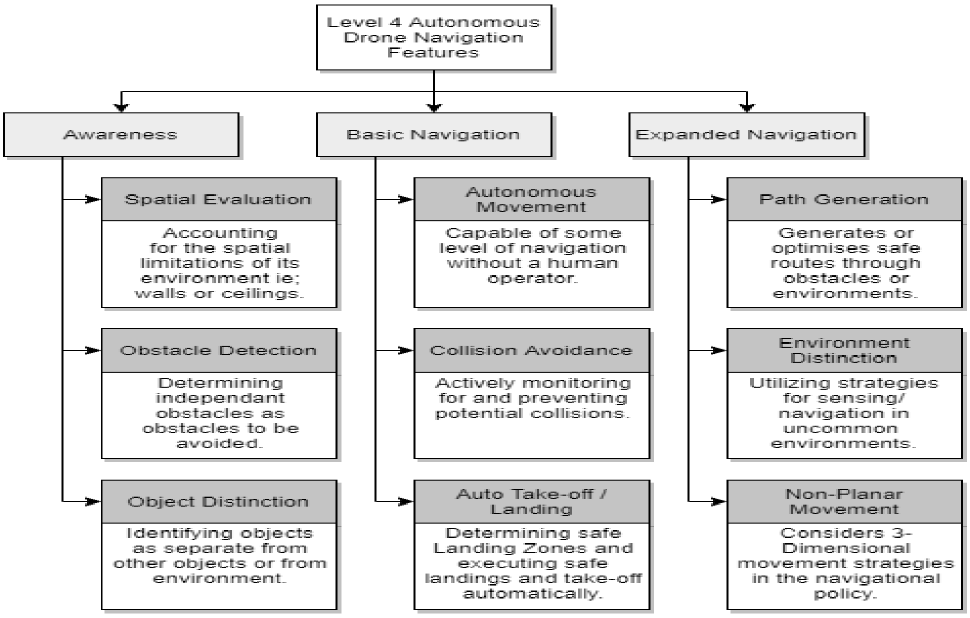

A surprising result from the comparative analysis shows that there were few research projects with the environmental distinction feature. Of those that do, no project attempted to distinguish explicitly between two or more environments. Several projects did test their given implementations in various environs, but did not qualify as addressing the environmental distinction feature, as their approach did not provide consideration for the differences in those environments to be represented in the solution itself. There is no architecture modification to consider different environments, and there are no datasets

SAE Level	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5 (Ideal)
Summary of Level	No Automation	Automated Assistive Features, Operator Navigates	Automated Navigational Features, Operator Monitors	Automated within some cases, Operator Intervenes	Automated within most cases, Operator is Optional	Automated within all cases, Operator is Unnecessary
Spatial Evaluation		✓	✓	✓	✓	
Obstacle Detection		✓	✓	✓	✓	
Object Distinction			✓	✓	✓	
Autonomous Movement			✓	✓	✓	
Collision Avoidance	N/A		✓	✓	✓	N/A
Envronment Distinction				✓	✓	
Non-Planar Movement				✓	✓	
Auto Take-Off/Landing					✓	
Path Generation					✓	

4. RESULTS AND DISCUSSION

The system is built using drone, minimizing the limitations associated with robots that are static. The use of drone makes the system more efficient than robots that have failed in disastrous conditions like the earthquake because when humans get stuck underneath the debris it makes it difficult for the robots to walk over the broken and ruined buildings. It is a real time autonomous drone technology system which is proposed for detecting humans in disastrous conditions and intimating the rescue team about the exact positions of the effected human.

Quadcopter system works on the principle of air lifting phenomena with high pressure. The propellers force the air in downward with high pressure due to which an uplift force is created and as a result action reaction law is applied on the whole system. When this uplift force dominates the earth's gravitational force, the whole system start flying in the air. But there is a problem with the rotation of propellers. If we rotate the propellers in clock wise direction then due to this rotation, a torque will be applied over the whole system in one direction .And similarly if we rotate the propellers in anti-clock wise direction then also a torque will be produced over the whole system and the whole system will start rotating anticlockwise. To overcome this problem we rotate two propellers in clockwise direction and remaining two propellers in anticlockwise direction. This phenomenon produces torque in opposite direction and they get balanced and the system remains stable while flying.

5. CONCLUSION

Nowadays we see various types of natural calamities are being observed during recent years. These natural calamities cause impact on many buildings as well as to the human lives.The vulnerability is more in densely populated areas where the bad strike can lead to greater damage as well. To save these lives our rescue personnel faced many problems. They are unable to locate the victims of the disaster. So we came up this idea which can help the rescue personnel to locate the victims during unfortunate disastrous situation. Also it can actually help them to rescue the victim fastly. Our project basically comprises of a drone and human sensor which can easily locate the position as well as it is able to fly at that place where it is quite difficult to reach. We are trying to made prototype of this idea so it can help the rescue personnel in their mission to save lives.

Natural calamities have recently opened their doors to disasters which in turn have affected various regions of the world. Disasters serve as an eye-opener as they are unstoppable and exceptional events which are either natural or manmade, such as earthquakes, wildfires, floods and terrorist attacks etc. These natural catastrophes many a times serve as a hats down chink in the armor as they lead to a massive death toll either because of people being stuck in the debris or due to no help received on time. One of the major challenges faced by the rescue and search teams during a massive disaster is the actual search of survivors and victims at the earliest and also reaching out to far off areas to make sure people are not stuck under the debris.

This paper presents a real time autonomous drone technology system named “Human Sensor On Drone” that is capable of detecting humans in disastrous conditions. This system assists in the rescue process by identifying the exact location of the survivors at the earliest. As the system is a drone based system, it can easily be mobilized and controlled. This system comprises of a monitoring system along with a camera module and sensor unit to identify the existence of humans buried under the debris.

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