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Editorial

Control and Position Tracking for UAVs

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1. Introduction

There has been exponential development of UAV technology and related research areas such as artificial intelligence, which will raise UAVs' ability for autonomous flights to a higher level. Drones have become more common and accessible than a decade ago. Commercial drones, which can be bought by anyone, are equipped with advanced functionality allowing them to track and recognize humans and record high-quality amateur videos. Creating 3D presentations in the sky with the use of hundreds or even thousands of drones with RGB LED lights in a large swarm has become a normal form of present-day entertainment. In addition, military UAVs can make flights of several hours over a range of hundreds of kilometers, even without GNSS signals, using only visual navigation. Despite those obvious achievements, there is still a research area considered to be challenging, i.e., position or trajectory tracking, in particular, for practical applications of tasks in which a UAV tracks a target with similar dynamics, such as other UAVs, or moves along a predefined trajectory shape. The issues that limit the practical use of position-tracking algorithms are related mostly to the sensing equipment responsible for the localization of UAVs and tracked targets. Therefore, most of the current research focuses on the problem of optimal path planning and tracking for specific types of UAVs and environments.

A comprehensive comparison of all recent local and global path planning methods that can be applied to a single UAV or a swarm of UAVs is presented in [1]. Among local path planning algorithms, the following can be listed: artificial potential field (APF) [2,3], dynamic window approach (DWA) [4,5], mathematical optimization algorithm (MOA) with the use of mixed integer nonlinear and linear programming or dynamic programming [6], and finally, model predictive control (MPC) [7]. All these local path planning algorithms belong to a set of dynamic programming algorithms. Finding optimal trajectories is carried out dynamically only in the local time horizon, in the area with local obstacles having sensor data collected in real time. In contrast, global path planning algorithms are static programming algorithms that are based on known maps of surroundings to find optimal trajectories between starting and ending points. They can be split into two subgroups: traditional and intelligent algorithms. Traditional algorithms are deterministic, which include Voronoi diagrams (VD) [8], the Dijkstra algorithm (DA) [9], rapid exploration random tree (RRT) [10], probabilistic road map (PRM) [11], Dubins curves (DC) [12], the Floyd algorithm (FA) [13], and the fast marching method (FMM) [14]. Intelligent algorithms are mostly bio-inspired heuristic algorithms and those based on machine learning. Heuristic methods include the following algorithms: the A* algorithm [15], evolutionary algorithms (EA) [16], the simulated annealing algorithm (SAA) [17], particle swarm optimization (PSO) [18], the pigeon-inspired optimization algorithm (PIO) [19], the fruit fly optimization algorithm (FOA) [20], the artificial bee colony algorithm (ABC) [21], the salp swarm algorithm (SSA) [22], ant colony optimization (ACO) [23], the grey wolf optimizer (GWO) [24]and the harmony search (HS) [25].

These mentioned approaches and methods provide a broad area for further research on position control and tracking. However, they are focused mainly on path planning and its optimization. This can be achieved under the condition that knowledge of the UAV's dynamics and an approximate map of the area, where the UAV will fly, is available.

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Searching for an optimal path between the starting and ending points through a complex environment can take time; therefore, many algorithms are used offline, and the results must be known at least by the moment of takeoff. The challenging case is to determine the optimal path in an unknown environment in real time. Another interesting issue to be solved and researched is an algorithm that allows the tracking of another object with completely different dynamics than UAVs, which moves through unknown paths. The optimization and planning of the flight paths of UAVs' swarm through a complex terrain with narrow corridors is also a major contribution to the research area related to this Special Issue, and it should be considered in future research.

2. An Overview of the Published Articles

Maciej Salwa's article (contribution 1) discusses the optimal control of a tricopter UAV in programmed flights. In the study, a new approach to PID loop tuning is presented and investigated to achieve the desired performance of the tricopter by finding the optimal coefficients of the PIDs. The proposed method is effective for performing repeatable flights through predefined paths. The basis of the method is a control quality criterion, which is based on the integral of the absolute error, and its minimization allows finding the optimal PID coefficients. The authors conclude that their method could be an alternative to methods based on adaptive control, as they provide the same reliability and robustness of the control system. The results of the numerical simulations confirm that the tricopter control achieves the desired performance causing a minimal tracking error and a satisfactory short response time.

The article by Cezary Kownacki and others (contribution 2) presents results from experimental research on a multicopter tethered to the ferry deck during a normal cruise through the Baltic Sea. The main goal of the research is to synchronize the movement of both the UAV and the landing pad on the ferry to enable take-off, flight, and landing without stopping the ferry, which takes time in maritime conditions. To achieve this, a special landing pad navigational station was developed with two GNSS receivers and an electronic compass, which sends the navigational parameters of the landing pad over the radio link to the onboard computer of the UAV. The Kalman filter based on the navigational parameters of the UAV and the ferry can estimate the position of the landing pad even when the radio link is lost. During the experiment, several flights were performed, and any unnecessary power cord unwinding was not observed, whether from tension from tracking errors or wind gusts. In the tests, the power cord unwinder was also examined with automated tension control.

The article by Zbigniew Banaszak (contribution 3) describes the maintenance of offshore wind farms, using a fleet of UAVs. In the research, proactive and reactive path planning was presented and validated through numerical simulations. Here, proactive path planning means finding an optimal schedule at a pre-mission phase for the inspection and the service of wind turbines on the farm made by service teams with the support of the UAV. Reactive path planning for UAVs is performed during farm maintenance if the support teams request a spare part to be delivered, considering that the vessel's position, planned route, and weather conditions are known. The UAV fleet is used to deliver the required spare parts to each service vessel. The main goal of proactive path planning for the service vessels and the fleet of UAVs is to shorten the total service time as much as possible. The authors claim that the model of proactive and reactive path planning and scheduling is easy to generalize and expand with the vessel routing and staff and competence planning.

The article by Panagiotis S. Trakas (contribution 4) is dedicated to the control of the longitudinal motion of a small fixed-wing UAV during the landing phase, which is robust against external disturbances and allows for avoiding the stalling effect by imposing prescribed state constraints. To design an effective controller to track the altitude and airspeed trajectories in the landing phase, a combination of the adaptive prescribed performance control and saturation of the generated state reference trajectories of the flight-path angle, the pitch angle, angle of attack, and pitch rate is considered. One of the advantages of the proposed method is that it is approximation-free, which means that any knowledge about system nonlinearities or any disturbance observer is not obligatory. To verify the effectiveness of the novel APPC (Adaptive Prescribed Performance Control), numerical simulations were conducted, including scenarios of external disturbances responsible for inducing chattering in the desired control input, as well as comparison of the results to standard PID control loops and the P-PPC scheme (hybrid Proportional and Prescribed Performance Control). The proposed robust adaptive control scheme deals with the conflicting nature between the output specifications, inputs, and state constraints of the system, which is crucial for guaranteeing the safety and the stability of UAV navigation during landing. This is possible due to the exploitation of the adaptive performance boundaries and adaptive performance trajectory tracking with predefined characteristics.

The article by Gangsong Ding and others focuses on distributed airborne radar, which, in contrast to distributed ground-based radar, has stronger anti-damage ability, more degrees of freedom, and a better detection view of targets. A UAV formation is used as a carrier of airborne radars; thus, stable wireless communication in the formation is essential to maximize the radar detection performance. Applying multi-relay methods directly in the case of long spacings between UAVs can result in wireless network overload and a long time delay. In the article, the measurement of the angles of arrival (AOA) made by each UAV in the swarm is considered to create a passive localization model of an active target. To maximize the accuracy and to achieve the optimal performance of radar localization under inter-UAV communication constraints, i.e., communication coverage, and topology, the authors propose applying a joint radar-communication optimization algorithm (JRCO). The algorithm is fully distributed, and this enables it to simultaneously sense the information of a UAV in the neighboring area and to co-decide in the same time slot. Based on two sets of parameters for four different control groups and one experimental group, numerical simulations of the JRCO algorithm were performed, each changing the communication coverage range, as well as different approaches to optimize UAV locations. Plots of the MSE (Mean Square Error) of the AOA measurements confirm the effectiveness of the JRCO for the experimental group.

The next article by Ahmed Alshahir and others (contribution 6) considers 2D dynamic visual servoing, where a UAV tracks a ground vehicle, using a single camera facing down toward the ground. To track a ground vehicle like a car, there is no need to use data about orientation angles since the camera is mounted with a gimbal framework, as well as knowing the flight altitude. Control is based on the knowledge of the x and y axes' displacement and difference in heading angle, and the concept of differential flatness is applied to extract and demonstrate that it is possible to control a UAV using this knowledge. The proposed dynamic 2D visual servoing method (Dynamic IBVS) allows generating movements for the quadcopter in real time and solves the problem related to the fact that the quadcopter is an under-actuated system. The effectiveness of the proposed approach in tracking ground vehicles is proved in numerical simulations. The processing of images from the camera, the related delays, the disturbances in control of the gimbal with the camera, and the motion of a ground vehicle on an uneven surface are not considered by the authors. These issues would have a significant impact on the effectiveness of the approach in real-world applications.

The final article (contribution 7) by Azmat Saeed and others concerns a method of linear matrix inequalities (LMIs)-based linear parameter varying (LPV) control for quadrotors with time-varying payload. The novelty of the article is provided by a new 6DoF LPV model of the quadrotor, which considers the mass, inertia, and mass flow rate as variables, and it is applicable for large tilt angles and scenarios with wind disturbance. It was developed with the use of a curve fitting tool and a triangle polytope to reduce the number of vertices. The problem of time-varying payload is more important for quadrotors because of the fact that it directly affects the vehicle dynamics through a changed mass, the position of the mass center, and moments of inertia; therefore, an adequate control scheme is required. The LPV control scheme designed for the LPV model of a quadrotor based on the LMI results in robust stability and quadratic H_∞ performance. The 3D CAD model of the quadrotor was developed with the use of SOLIDWORKS, and the time-varying payload was simulated as a liquid tank mounted under the quadrotor with different water levels. The effectiveness of the proposed control scheme was verified through numerical simulations simultaneously comparing it with the LTI control scheme. The results confirmed the possibility of the control scheme's usage in such applications where the quadrotor payload is changing in time like fire-fighting UAVs or agricultural drones used in crop spraying. Therefore, it would be interesting to also see experiments with a real quadrotor.

3. Conclusions

The articles published in this Special Issue of *Applied Science* entitled "Control and Position Tracking for UAVs" provide a broad cross section of the issues that are crucial for real-life tasks for quadrotors, like firefighting, crop spraying, monitoring areas around vessels to secure them against collisions, the maintenance of offshore wind farms, creating an early-warning system based on distributed airborne radar, suspicious ground-vehicle tracking in intelligence tasks, and many others. All these topics and the relevant algorithms are presented by the authors. The diversity of algorithms presented in this Special Issue shows the range of meanings of the phrase "control and position tracking". Most of the articles presented numerical simulations, and real world experiments are needed. Considering real-world applications can be challenging due to the limitations of UAV technology, especially when addressing the accuracy of onboard measurement systems, data processing, and the calculation performance of onboard computers, as well as the robustness against external disturbances. Although UAV technology is continuously improving, most commercial drones still rely on standard PID loops as a well-known and easy-to-use control scheme.

The gap between the research that provides control schemes that are more robust and effective in trajectory-tracking applications and the possibilities of ready-to-use UAVs should be filled with research including prototyping, implementation, and experimental verifications to make these control schemes the state of the art in reality. As stated in the introduction, there are many approaches to finding optimal paths in local and global horizons, with or without a map of the environment and with or without a model of UAV dynamics, whether deterministic or heuristic. Global path planning algorithms depend on the possession of detailed information of a map to explore all possible paths, and this implies requirements for measurement systems and the use of a SLAM technique. Being based on predefined maps significantly limits the usage of these algorithms in unknown areas. In turn, in most cases, local path planning algorithms require knowledge about both the robots and target dynamics models, and they are also sensitive to the accuracy of measurements and those models, external disturbances, and the costs of computations in real time.

In conclusion, there is still a broad area in which to perform research on control and position tracking using unmanned aerial vehicles, especially if artificial intelligence and deep and machine learning become common and universal tools that will be able to eliminate the weaknesses of traditional approaches and make them more robust against insufficient knowledge, time-varying and unknown parameters, or unexpected flight scenarios.

Conflicts of Interest: The author declares no conflicts of interest.

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