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The development of an autonomous navigation system with optimal control of an UAV in partly unknown indoor environment☆

Thi Thoa Mac[*,a,b], Cosmin Copot[c], Robin De Keyser[a], Clara M. Ionescu[a]

[a] DySC research group on Dynamical Systems and Control, Ghent University, Technologiepark 914, Zwijnaarde 9052, Belgium
[b] School of Mechanical Engineering, Hanoi University of Science and Technology, Dai Co Viet street 1, Hanoi, Vietnam
[c] Department of Electromechanics, Op3Mech, University of Antwerp, Groenenborgerlaan 171, Antwerp 2020, Belgium

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ABSTRACT

This paper presents an autonomous methodology for a low-cost commercial AR.Drone 2.0 in partly unknown indoor flight using only on-board visual and internal sensing. Novelty lies in: (*i*) the development of a position-estimation method using sensor fusion in a structured environment. This localization method presents how to get the UAV localization states (position and orientation), through a sensor fusion scheme, dealing with data provided by an optical sensor and an inertial measurement unit (IMU). Such a data fusion scheme takes also in to account the time delay present in the camera signal due to the communication protocols; (*ii*) improved potential field method which is capable of performing obstacle avoiding in an unknown environment and solving the non-reachable goal problem; and (*iii*) the design and implementation of an optimal proportional - integral - derivative (PID) controller based on a novel multi-objective particle swarm optimization with an accelerated update methodology tracking such reference trajectories, thus characterizing a cascade controller. Experimental results validate the effectiveness of the proposed approach.

1. Introduction

In the last few years, Unmanned Aerial Vehicles (UAVs) stir up both scholar and commercial interest within the robotics community as the real and potential applications are numerous [1]. To undertake the challenging task of autonomous navigation and maneuvering, a versatile flight control design is required.

A large number of studies have emerged in the literature on UAVs. Some examples of its application can be found in precision agriculture [2], formation control of Unmanned Ground Vehicles (UGVs) using an UAV [3], habitat mapping [4]. Modeling, identification and control of an UAV using on-board sensing are presented in [5]. Catching a falling object using a single UAV, has been accomplished in [6] and for a group of UAVs in cooperative formation in [7], where high-speed external cameras were applied to estimate the position of both the objects and UAVs. Simultaneous localization and mapping (SLAM) was implemented to navigate UAV in working space [8]. Current implementations in UAV still require collision avoidance, adaptive path-planing and optimal controller. There exists a need to design methodologies to cope with these requirements to increase the degree of intelligence and therefore autonomy of UAV.

An autonomous UAV consists of four essential requirements: (i) *perception*, the UAV uses its sensors to extract meaningful information; (ii) *localization*, the UAV determines its pose in the working space; (iii) *cognition and path planning*, the UAV decides how to steer to achieve its target; (iv) *motion control*, the UAV regulates its motion to accomplish the desired trajectory.

The path planning problem can be divided into classical methods and heuristic methods [9]. The most important classical methods consist of cell decomposition method (CD), potential field method (PFM), subgoal method (SG) and sampling-based methods. Heuristic methods include neural network (NN), fuzzy logic (FL), nature inspired methods (NIM) and hybrid algorithms. The potential field method (PFM) is particularly attractive since it has a simple structure, low computational complexity and easy to implement. In literature, there has been a significant amount of work based on this method applied to ground agents path planning [10–13]. An interesting work on implementing and flight testing of this approach on an UAV is studied in [14]. To operate in real-time, a layered approach is developed in uncharted terrain: plan globally and react locally. The global planner is based on an implementation of Laplace equation that generates a potential function with a unique minimum at the target. The local planner uses modification of

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[*] Corresponding author.

E-mail addresses: Thoa.MacThi@ugent.be (T.T. Mac), Cosmin.Copot@uantwerpen.be (C. Copot), Robain.Dekeyser@ugent.be (R.D. Keyser), ClaraMihaela.Ionescu@ugent.be (C.M. Ionescu).

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conventional potential field method in which not only the position of the UAV (as in the traditional PFM) but also the relative angles between the goal and obstacles are taken into account. However, this approach sometimes encounters problems when the repulsion from obstacles exceeds the physical constraints of the UAV. It is pointed out that the potential field method has several inherent limitations [15] in which the non-reachable target problem is the most serious one and is worth investigating since it causes an incomplete path in the navigation task.

As an UAV is a complex system in which electromechanical dynamics is involved, the robust controller is an essential requirement. In [16], the dynamical characteristics of a quadrotor are analyzed to design a controller which aims to regulate the posture (position and orientation) of the quadrotor. An autonomous control problem of a quadrotor UAV in GPS-denied unknown environments is studied [17,18]. In order to obtain reasonable dynamical performance, guarantee security and sustainable utilization of equipment and plants, controller performance has to be constantly optimal.

In the current study, a real-time implementation for an AR. Drone 2.0 UAV autonomous navigation in indoor environment is proposed to trigger its identification, able to estimate the UAV pose, detect obstacles, generate the suitable path and to perform the parametric optimization of its optimal proportional-integral-derivative (PID) controller. The main contributions are the development of: (*i*) a position-estimation method based on sensor fusion using only on-board visual and inertial sensing considering the time delay of the camera signal and reducing drift errors; (*ii*) a solution to solve the non-reachable target problem in conventional PFM; (*iii*) multi-objective optimization PID controller based on a proposed multi-objective particle swarm optimization (MOPSO) with an accelerated update methodology to execute navigation task. The motivation behind this research is to illustrate that autonomous navigation is feasible on low-cost UAV devices.

This paper is structured as follows: the next section gives a description of AR.Drone 2.0, identification, system setup and localization. Section 3 discusses UAV path planning based on improved potential field method. Multi-objective particle swarm optimization algorithm for control parameters optimization and simulation results are described in detail in Section 4. Next, the effectiveness of the proposed real-time collision-free path planning for an AR. Drone 2.0 UAV using only on-board visual and inertial sensing application in indoor environment is presented in Section 5. The final section summarizes the main outcome of this contribution and presents the next challenges.

2. System setup, identification and localization

A description of the Ar.Drone 2.0 main characteristics, system identification, sensory equipment, system setup and localization are presented in this section.

2.1. Ar.Drone 2.0 description and coordinates system

There are four basic motions of this UAV: pitch, roll, throttle, yaw and translational movements over *x, y* and *z*, as shown in Fig. 1 **(Left)**.

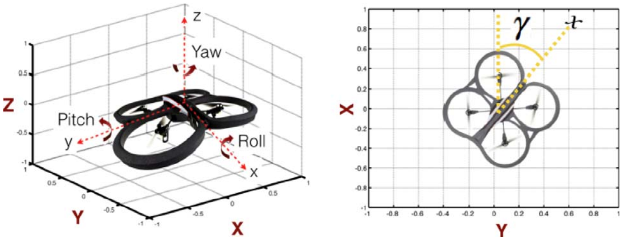

Fig. 1. The movements of an AR.Drone 2.0 in absolute and relative planes **(Left)** and UAV displacement on (*x; y*) plane respect to the absolute plane **(Right)**.

It is worth mentioning that the coordinate system described above (*x; y; z*), represents a relative coordinate system used by the internal controllers (low layer). Using such a coordinate system instead of absolute coordinates (*e.g.*, *X; Y; Z*) in the high layer will yield errors. For example, notice that by rotating the quadrotor, the relative coordinates (*x; y*) will change with respect to the absolute coordinates, as depicted in Fig. 1 **(Right)**. In which, the rotation angular of *XY* coordinate system respect to the absolute *xy* coordinate system is γ. It is possible to state that the relation between the two-coordinate system depends directly of this angle.

The IMU provides the software with pitch, roll and yaw angle measurements. Communication between Ar.Drone and a command station is performed via Wi-Fi connection within a 50 m range. AR.Drone 2.0 is equipped with two cameras in the bottom and in frontal parts with the resolutions of 320 × 240 pixels at 30 frames per second (fps) and 640 × 360 pixels at 60 fps, respectively.

2.2. Analysis of inputs and outputs and system identification

The developed Software Development Kit (SDK) mode allows the quadrotor to transmit and receive the information roll angle (rad), pitch angle (rad), the altitude (m), yaw angle (rad) and the linear velocities on longitudinal/transversal axes (m/s). They are denoted by $\{\theta_{out}, \phi_{out}, \zeta_{out}, \psi_{out}, \dot{x}, \dot{y}\}$ respectively. The system is executed by four inputs $\{V_{in}^{x}, V_{in}^{y}, \dot{\zeta}_{in}, \dot{\psi}_{in}\}$ which are the linear velocities on longitudinal/ transversal axes, vertical speed and yaw angular speed references as depicted in Fig. 2.

An Ar. Drone is a multi-variable and naturally unstable system. However, due to the internal low layer control implemented in the embedded operative system, it is considered as a Linear Time Invariant (LTI) System, which is able to be decomposed into multiple single input single output (SISO) loops. Transfer functions are obtained via parametric identification using the prediction error method (PEM) and Pseudo-Random Binary Signal (PRBS) input signals [19]. A sampling time of 5 ms for yaw and 66 ms for other degrees of freedom are chosen based on the analysis of dynamics characteristic. The identified transfer functions are given in Eq. (1).

Validation of transfer function of pitch/roll, altitude and yaw are presented in Fig. 3. The validation of the transfer function is made against a different set of data to prove that quadrotor movements are approximated appropriately.

$$\begin{aligned}
H_x(s) &= \frac{x(s)}{V_{in}^{x}(s)} = \frac{7.27}{s(1.05\,s+1)}\\
H_y(s) &= \frac{y(s)}{V_{in}^{y}(s)} = \frac{7.27}{s(1.0fs+1)}\\
H_{altitude}(s) &= \frac{\zeta_{out}(s)}{\dot{\zeta}_{in}(s)} = \frac{0.72}{s(0.23\,s+1)}\\
H_{yaw}(s) &= \frac{\psi_{out}(s)}{\dot{\psi}_{in}(s)} = \frac{2.94}{s(0.031\,s+1)}
\end{aligned} \tag{1}$$

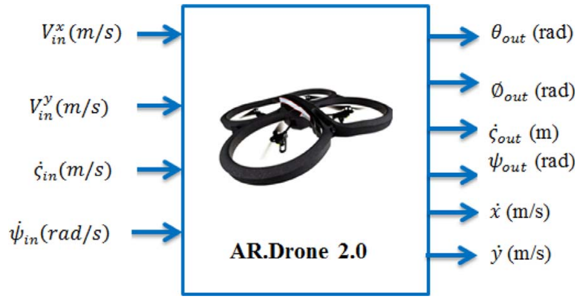

Fig. 2. Inputs and Outputs of an AR.Drone 2.0.