Design and Control of Drones

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Abstract

The design and control of drones remains an area of active research, and here we review recent progress in this field. Design objectives and related physical scaling laws are discussed, focusing on energy consumption, agility and speed, and survivability and robustness. Control of such vehicles is broken into low-level stabilization, and higher-level planning such as motion planning, and we argue that a highly relevant problem is the integration of sensing with control and planning. Lastly, we describe some vehicle morphologies, and the trade-offs that they represent. We specifically compare multicopters with winged designs, and the effects of multi-vehicle teams.

Contents

1. Introduction

Dramatic reductions in cost and advances in sensing technologies, actuation, energy storage, and computation have made drones commonplace. Their applications range from remote sensing to physical interaction, structural inspection to package delivery. Larger drones may also serve to carry human passengers, either for recreational purposes, or as aerial taxis and urban transit (often called Advanced Air Mobility or Urban Air Mobility, see e.g. (1)). Compared to many other types of robots, the operation of drones is complicated by (a) their typically unstable flight dynamics, where there is no simple "safe" behavior in the case of a fault; (b) the mass constraint making all designs highly integrated, and requiring economy of both actuators and sensors; and (c) severe energy consumption constraints.

In this paper we review the current state of the art of the design and control of drones. We focus primarily on multicopter drones, i.e. drones that rely on multiple rigid propellers whose speed is varied to produce variable thrusts, and where differences in thrusts produce torques to cause the vehicle to change orientation. This class of vehicle is popular, compared to more conventional aeronautical designs such as helicopters or fixed-wing aircraft, because of their extremely low mechanical complexity (in the case of a quadcopter, having only four moving parts, identical up to a mirror symmetry). Moreover, they are capable of hover flight, have well-understood control properties, and are typically very agile. The use of multiple independent rotors for large scale vehicles is typically called distributed electric propulsion, and promises increased efficiency and robustness (see, e.g., (2)). We note that the multicopter design is a century old, with one design from 1924 shown in Figure 1 – although the lack of passive stability meant that modern electronics were required to make them successful.

We start by recapitulating the key dynamic properties of drones, and then describe some typical, high-level design objectives. As with any engineered system, any given design represents a trade-off between various performance objectives and overall system cost. The first objective is usually to achieve acceptable range or endurance to complete useful missions. This is achieved by a combination of energy storage and efficiency. We describe some fundamental physical characteristics that capture, to a first approximation, the main

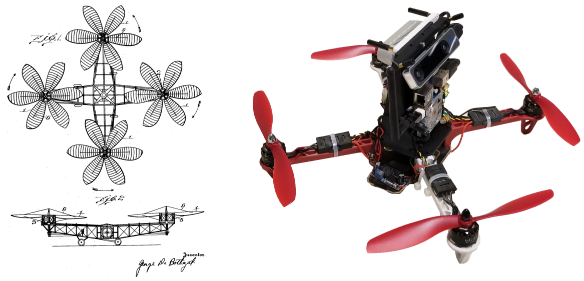

Figure 1

(left) A patent drawing from De Bothezat's 1924 patent (taken from (3)), and (right) a typical custom-assembled research quadcopter (taken from (4)).

trade-offs and limitations for drones. We relate the size and mass of a drone to its energy consumption, and show that hovering drones have a fundamental limitation on achievable flight time, given a fixed size and payload mass, independent of the available energy storage capacity.

Next we discuss both low-level control strategies, and higher-level motion planning. We note an emphasis on strategies that explicitly take sensors into account, allowing for reasoning (e.g.) about the effect of control actions on uncertainty. Finally we describe typical vehicle design morphologies, spending most time describing multicopters, but also briefly touching drones with wings and teamed systems.

2. Drone dynamics, design objectives, and scaling laws

In this section we provide a brief overview of the dynamics that govern drone flight, and then describe how typical design objectives are affected and traded-off.

2.1. Drone dynamics

We focus on the dynamics of multicopter drones near hover, and describe this only at a high level. Common multicopters are equipped with brushless motors that drive rigid propellers. The propellers typically have two propeller blades, though propellers with three or more

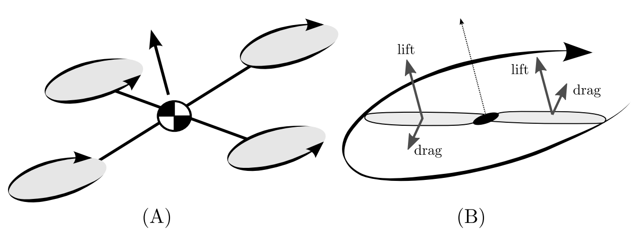

Figure 2

(A) A typical multicopter with four propellers, sharing a common thrust direction indicated by the arrow. (B) Each propeller produces both a total thrust force (due to the total lift of the blade elements) and a torque opposing its rotation (due to the couple of the drag forces on the blades).

blades are also possible. A higher number of blades typically allows for greater thrusts at the same rotational speed, but the relationship to power consumption, noise levels, vibration, etc. can be complex, see e.g. (5). As the rotating propeller displaces air, it produces both a force and a torque. The force is dominated by the lift, the component parallel to the axis of rotation. The force and torque components in the plane of rotation tend to be much smaller than those parallel to the axis of rotation – due to the rotational symmetry of the propeller, these are typically present only when the propeller is translating through the air. Fig. 2 shows a diagram of a quadcopter, and a propeller with two blades.

Being an aerodynamic force, the thrust is well approximated as proportional to the square of the angular velocity of the propeller, where the proportionality constant captures properties of the the propeller (e.g. shape and size), and the environment (specifically the air density, with which aerodynamic forces scale linearly to a first approximation). Opposing the rotation of the propeller is a torque parallel to the axis of rotation, caused by the couple of aerodynamic drag on the propeller blades, opposing their motion. This reaction torque is therefore also reasonably approximated as quadratic in the propeller angular velocity, though it is usually written as proportional to the thrust force the propeller produces.

For a translating propeller, there will also be components of torque in the propeller's plane of rotation, however these components are usually negligible compared to the moment caused by the thrust acting at a distance from the center of mass. More complex propeller thrust and torque models exist, e.g. in that of (6) used for high-precision control in agile flight, or the models of (7) for propellers in forward flight.

A typical multicopter is equipped with an even number of propellers, with parallel axes of rotation, but divided evenly in clockwise- and counter-clockwise rotations. Translational motion of the vehicle is achieved by pointing the common thrust direction so that the vector result of the thrust, weight, and aerodynamic forces on the vehicle produce a desired translational acceleration. As the propeller thrust forces are all parallel, the vehicle's translational acceleration is dependent only on the sum of the motor forces rather than their individual values. Near hover, in wind-free environments, the translation of a multicopter can be simply described as the result of the weight, and a single "total thrust" vector, greatly easing planning and control.

To rotate the vehicle, torques are produced by differences between the motor forces. The torque caused by the thrust acting at a distance from the vehicle center of mass causes the thrust vector to rotate (i.e. the roll and pitch motion). Rotation about the thrust vector is produced by differences in the propellers' reaction torques, noting that at hover the balanced number of propellers thus produces zero net reaction torque. In typical operations, the net angular momentum of the propellers is zero, again due to the balanced number of propellers. It should be noted that changes in the propeller speeds will also cause angular acceleration of the main body of a drone, through conservation of angular momentum; this effect is however typically negligible compared to the aerodynamic torques.

The control of a multicopter is thus achieved by specifying four quantities: the total thrust magnitude, and the three components of torque. For this reason, a hover-capable multicopter requires at least four propellers (though relaxation of the definition of "hover" allows for vehicles with as few as one propeller (8, 9)). Most drones (even those with six or more propellers) are therefore underactuated, with four control inputs for their six degrees of freedom (though exceptions are discussed later). A more detailed description of quadcopter dynamics may be found in, for example, (10).

Fixed-wing and hybrid vehicles are equipped with non-rotating lifting surfaces, and potentially associated control surfaces like ailerons, elevators, and rudders. In narrow regimes, the forces and torques produced by these are typically accurately modelled as quadratic in airspeed; however their modelling is greatly complicated when operated through extreme conditions such as stall and/or very large angles of attack. A good overview of fixed-wing aircraft modeling and dynamics is given in (11).

2.2. Design objectives and scaling laws

We explore some of the main criteria that influence the design of a drone, and discuss some fundamental scaling laws that govern their trade-offs. Specifically, we explore energy consumption (which affects range and endurance), agility and speed, survivability and robustness, and cost/complexity. As is typical of aerospace applications, drone designs are highly integrated and typically represent a compromise between competing objectives. A primary concern with any flying machine is its overall mass – shaving off mass from a design typically improves a vehicle's capabilities in many design objectives simultaneously.

2.2.1. Energy consumption. For missions involving surveillance, a primary design objective is flight time; for missions involving transportation it is range. For a fixed energy storage technology, these are determined by a vehicle's power consumption. When operating at low airspeeds, a drone's lift is produced directly by its propellers, whose power consumption can be approximated with actuator disk theory – an idealized propeller that is not translating, and operating in an inviscid, incompressible fluid will consume aerodynamic power that is inversely proportional to the radius of the propeller, and proportional to the force to the power of 1.5 (for details, see (11)). Thus, all else being equal, a vehicle equipped with larger propellers is thus expected to have better flight endurance. Simililarly, a vehicle requiring lower thrust (e.g. due to lower overall mass) will also have better endurance. The super-linear increase in power increases as the thrust increases implies that there is a point at which adding more battery capacity to a system actually decreases the system's flight time (12), due to the stored energy growing linearly in the mass used for energy storage.

2.2.2. Agility and speed. In applications such as drone racing (see, e.g., (13, 14, 15)) the primary objective is speed and agility. During constant velocity flight, the vector sum of vehicle weight, thrust force, and drag force is zero. All else being held equal, the maximum horizontal speed of a vehicle can be increased by reducing its mass, increasing the available

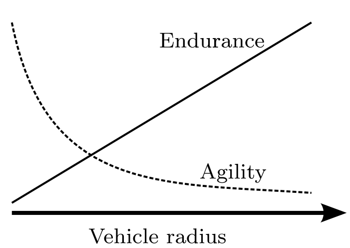

Figure 3

Approximate trade-off of efficiency and agility with vehicle linear size (at constant mass) for a multicopter.

thrust, or decreasing the aerodynamic drag force.

As the translational motion of a multicopter is dominated by the thrust vector, the ability to rapidly alter orientation is crucial to agility. For a vehicle with fixed components and overall mass, the highest agility comes from placing the propellers as close to the vehicle center of mass as possible. Though the torque required for attitude control will increase linearly as the propellers are moved farther from the vehicle center of mass, this effect is counteracted by the quadratic relationship between radius and mass moment of inertia. As the overall mass moment of inertia is typically dominated by the massive motors located at a large distance from the vehicle's center, the vehicle's attitude agility scales approximately inversely proportionally to its overall size. This is why multicopters are typically designed with the propellers placed as compactly as possible to the vehicle center. As smaller propellers can be arranged into a more compact design, there is a clear trade-off to be made between efficiency and agility. The trade-off between agility and endurance is shown schematically in Figure 3.

We briefly recapitulate the scaling argument of (16) to investigate the agility of vehicles as the size of all components is varied. Such an analysis requires assumptions on how achievable thrust force scales with rotor size; a difficult task especially as the scaling of the motor and batteries is typically difficult to capture simply. Two different approximations relating propeller aerodynamic scaling are given in (16), the first assuming that the Froude number (a dimensionless quantity relating flow speed to a characteristic length and the acceleration due to gravity) is constant, and the second assuming that the linear velocity of the rotor tip is constant (motivated by the requirement that the tip not break the sound barrier). These two alternate sets of assumptions lead to the conclusion that a multicopter's linear acceleration is either independent of scale, or scales proportionally to the vehicle's linear scale. The angular acceleration, however, scales either inversely proportional to the linear scale, or the square of the linear scale, depending on whether Froude or Mach scaling is used. For this reason, smaller and more compact multicopters are preferred in applications where agility is important.

2.2.3. Survivability and robustness. To operate in complex environments, especially near objects, requires either extremely precise control, or the ability to survive collisions. In the latter case the drone should be continue its mission with minimal interruption, which permits simpler control strategies, less precise sensors, etc. The additional structure required to reject disturbances comes of course with additional mass, with its related disadvantages. Because the structure must surround the vehicle, so that the added mass is typically far from the vehicle's center of mass, this tends to yield a significantly increased moment of inertia, which in turn corresponds to lower achievable angular accelerations.

3. Low level control and stabilization

A typical approach to architecting a control system for a drone is shown at the top-left of Figure 4, where a trajectory planner generates reference states, to be tracked by a low-level controller generating actuator commands. A separate state estimator uses sensor data to generate an estimate. Typically, the planner runs at a much lower frequency than the low-level control and estimator. This approach allows for the design each component in relative isolation, reducing both design complexity and computational cost; and potentially allowing for simpler arguments w.r.t. optimality. However, as increasing computational power

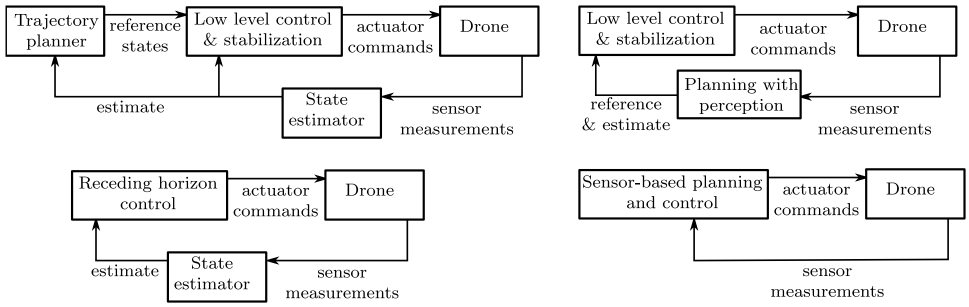

Figure 4

Various control system architectures.

becomes more available, tighter integration of components allows a designer to achieve more complex performance specifications (especially with respect to robustness and operation in complex environments).

A first step in this direction is the use of receding horizon control, where the trajectory planning is repeated at a very high frequency, and thus no separate trajectory tracking control is needed. Such approaches are especially valuable when operating in dynamic environments. Usually, state estimation remains separate from planning, and the control does not explicitly account for the sensing. Alternatively, the trajectory planner and state estimator can be combined, with the planner taking considerations of estimate quality and sensor modality into account. A separate low-level control allows the planner to run at a lower frequency still.

The final step is a single unified system, where the trajectory planner also explicitly takes sensor constraints and uncertainty into account. Although increasingly tight integration may lead to better performance, it is necessarily more specific to the system and application. In this section we consider the low-level control of a more loosely integrated architecture, while planning is discussed in the next section.

There is a significant amount of literature on control strategies for standard multicopters under nominal conditions. Their dynamics are captured well by relatively simple (though still nonlinear) equations, without complex (and often highly empirical) aerodynamic relationships as are typically required for winged systems. From the discussion in Section 2 it can be seen that the translational motion of a multicopter is dominated by its orientation, specifically the orientation of the thrust vector. If the orientation and total thrust can be regulated sufficiently quickly, the vehicle's acceleration can be treated as an input to a higher-level translational controller, yielding an approximate double-integrator system.

A first choice when designing an attitude controller is the representation used for the attitude, with popular choices including Euler symmetric parameters / quaternions (e.g. (17)), the rotation matrix itself (e.g. (18)), or rotation vectors (e.g. (19)). In a first order analysis, all approaches typically yield similar results, with differences only becoming apparent when recovering from large disturbances / orientation changes.

As these systems are pushed to more complex environments and to execute more challenging tasks, the typical assumptions of perfect state estimates and accurate model knowledge become limiting. One aspect of active research thus focuses primarily on systems with poorly understood dynamics, and another on accounting for greater errors in state estimation. In situations where accurate modelling is difficult, controllers that learn (either in advance, or adapt during operation) become attractive.

Carrying unpredictable payloads is one example where learning and adaptation may play a crucial role, so that the physical parameters required to evaluate the dynamics are unknown and potentially change over time. Gaussian processes are used in (20) to approximate system dynamics, with the adaption only occurring if the model error exceeds a threshold. Adaptive control provides another set of tools to approach such systems – in (21) an adaptive control approach based on Lyapunov analysis is presented to compensate for an unknown payload.

In some cases, robust control theory is used to overcome the uncertainty problem. The robust control approach guarantees a certain level of control performance under various environmental conditions by structured or lumped handling of system uncertainties, and ensures the stability of the system within the designed uncertainty range. Therefore, when robust control is applied to multicopter control, one can overcome parametric uncertainties such as mass and mass moment of inertia uncertainty, or unknown external disturbances such as wind or gust. A recent example is (22), wherein a robust control method satisfies the target performance even when the platform's total mass is unknown.

Another aspect of interest is the interaction between the drone's low-level control and state estimation. For example, stiffer controls requiring larger angular velocity are likely to cause motion blur, leading to poorer tracking using visual sensors. For this reason, it is of interest to design low-level control strategies that incorporate the sensing modality constraints. For example, in (23) a robust controller is designed for a multicopter using VIO for state estimation, where the robust controller is shown to provide improved performance in adverse lighting conditions, at the cost of conservative behavior in well-lit environments.

As drones are naturally sensitive to the ambient air conditions, there is significant effort made to identify the wind field around a drone and suitably compensate for it. In (24) a quadcopter is equipped with an onboard wind sensor to estimate wind fields in an urban environment. Similarly, in (25) a quadcopter with additional sensors estimates the local wind vector, the drag force on the vehicle, and external forces due to e.g. collisions.

Rather than using models, deep reinforcement learning can be deployed by relying on extensive data, as for example in (26) as an approach to react to cyberphysical attacks, avoiding the traditional approach of explicit fault detection and diagnosis.

4. Motion planning

Under nominal conditions, with the assumption of perfect state and environment knowledge, the generation of trajectories for drones through static environments is well-studied. See, e.g., (27) for a recent review. Approaches exploiting differential flatness yield trajectory generation schemes that are both high-performance and computationally tractable. However, generating motions through dynamic environments, without explicit advance knowledge of the environment, and with constrained sensing remains a very active area of research. Moreover, given the typically constrained computational resources available for small drones, an emphasis remains on computational efficiency. We consider, specifically, three aspects that can motivate the planning problem – planning while considering limitations of the drone's perception system, planning to avoid collisions in complex environments, and planning for energy considerations. Of course, many other objectives may be considered, e.g. privacy (e.g. (28)) or safety.

4.1. Planning for perception

In addition to creating trajectories that are dynamically feasible (e.g. do not require impossible inputs), and avoid collisions with obstacles, a growing amount of work additionally strives to create trajectories that account for the vehicle's sensor modalities. Because of size, weight, and power constraints, drones must make do with a minimum number of sensors, placing a greater emphasis on their optimal use. Increasing computational capability allows for more sophisticated algorithms, with more integration of specific sensor capabilities with vehicle control. An early example is the Perception Aware Model Predictive Control framework of (29), with more recent work including (30, 31, 32, 33). The primary sensor is typically a vision sensor, with the motion planner attempting to keep particular visual features inside the camera field of view as the vehicle maneuvers (29, 31, 32), or maneuvering the vehicle to avoid areas with little visual texture, where a VIO system is likely to lose tracking (30, 33).

A related planning problem is to generate motion that maximizes coverage of a target using a particular drone-mounted sensor. In this case, the vehicle motion is typically much slower, and the emphasis is on mission-level planning, rather than low-level stabilization. Some recent examples in this direction include (34, 35, 36) – in both (34) and (35) multiple UAVs are used to carry out inspections of large structures, using respectively heuristics or a greedy strategy to make the problem computationally tractable. The approach in (36) utilizes firstly a top-down view of the scene to be captured, generating a coarse model of the scene to generate paths.

To explore (and generate models/maps of) completely unknown environments represents another difficult challenge. Motivated by the challenge of exploring underground environments such as caves, (37) presents an imitation learning approach built from of a graph-based planner. The approach aims to move the drone so that an onboard depth sensor incrementally reveals the environment.

4.2. Collision avoidance

For most drones, any type of collision is associated with a very high likelihood of crashing, and the failure of the mission. Significant work already exists on planning in static and known environments, with the problem of motion planning through unknown or dynamic environments receiving increasing attention. Where the environment is not previously known, a particular emphasis is on exploiting properties of the drone's sensors, and especially on assumptions and simplifications that allow for computation in a sufficiently short time to be useful.

Depth cameras represent a very attractive sensor for motion planning applications, being relatively lightweight, inexpensive, and directly providing three dimensional information on the environment. In (38) a planning approach is given for a multicopter using a depth camera. Each frame of the depth camera is treated as a local map, through which collision-free trajectories are planned; where the plan is updated with each new depth frame in a receding-horizon fashion. To achieve sufficiently fast computation, the rectangular image of the depth sensor is specifically exploited, and the free space is represented using collision-free pyramids. A depth camera is also used in (39), where rays are projected from the vehicle into free space, to quickly detect collisions.

Using a library of trajectories, where those in collision can be quickly eliminated, trades some computational load for memory. Two recent examples of this are (40, 41). Because the motions are pre-computed, these methods may be faster to execute than those that rely on real-time computation of motions; however they are limited by the resolution of the precomputed motions.

Radar sensors may allow for detecting the relative velocity of obstacles, and may therefore be particularly suitable in dynamic environments. An example of a drone equipped with a millimeter wave radar is given in (42), which combines the radar with a monocular sensor to track obstacles using an extended Kalman filter, followed by motion planning using RRT* (43).

Event cameras, which record changes in the image (rather than the image itself) also hold much promise for dealing with dynamic environments. In (44) an event camera is combined with a deep neural net to enable a drone to dynamically avoid obstacles thrown at it, and in (45) an event camera-based high-speed dynamic object extraction technique is introduced where the drone can dodge incoming objects rapidly.

Where external sensing (such as motion capture) is available, the challenge of planning with dynamic obstacles is significantly simplified. In such scenarios, external computation can typically also be used, allowing for richer motion plans, and avoiding obstacles that are still beyond what is possible using onboard only sensing. For example, both (4, 46) allow a multicopter to avoid obstacles thrown at it from a short range.

4.3. Energy-focused planning

Given the importance of efficient use of the limited energy of a drone, there is also significant effort to take energy consumption into account when doing motion planning. The difficulty of creating accurate models of energy consumption means that approaches here tend to be model-free. In (47) an end-to-end reinforcement learning approach is used to plan to maximize coverage of an area for a given power budget; (48) uses extremum seeking control to adapt a vehicle's speed and sideslip to minimize power consumption in the face of varying payloads and environmental conditions. At a higher level, the motion planning can be combined with system design; for example (49) combines the placement of static battery charging stations with trajectory generation for aerial robotics.

5. Vehicle morphologies

Rapid prototyping tools like 3D printing facilitate experimentation with different vehicle morphologies, and a large variety are used depending on the requirements of the vehicle. In this section we review recent work on vehicle designs, specifically looking at multicopter design, drones with fixed wings, and vehicle teams.

5.1. Multicopters

Multicopters remain the most common drones, being mechanically extremely simple. They typically consist of an even number of propellers, symmetrically located around the vehicle center of mass; with the simplest design capable of hovering being a quadcopter as shown in Figure 2. Though simple, the quadcopter has the disadvantage of having no obvious redundancy in the event of a component failure, motivating the design of more complex multicopters featuring six, eight, or more propellers. Some examples of unconventional

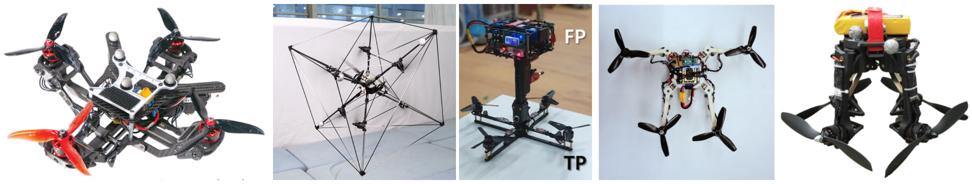

Figure 5

Various unconventional multicopter designs, from left to right (images taken from respective citations): the TiltDrone of (50), with motors on spherical joints, and the Omnicopter (51), equipped with eight motors, are both capable of fully actuated flight. The T^3-multirotor of (52) can shift its centre of mass by tilting the top platform, giving it the ability to maintain flight after the failure of a motor. Two shape-shifting drones are shown on the right, a foldable drone with actuated arms that move in the rotor plane (53) and a passively morphing drone, with no actuators beyond the four motors of a conventional quadcopter (54).

multicopters are shown in Figure 5.

By allowing the propeller thrust vector to rotate relative to the vehicle body, the system can be fully actuated and capable of moving independently of its orientation. In (50) a quadcopter is presented with motors mounted on spherical joints, so that the system can orient the four thrust vectors independently. Similarly, a hexacopter with tilted rotors is presented in (55): here the focus is on the capability of the vehicle to maintain stable flight in the face of an actuator failure. An approximately rotationally invariant multirotor is presented in (51), where the vehicle's eight propellers allow for ominidirectional thrusts and torques, fully decoupling translational from rotational motion.

Vehicles that can change their shape mid-flight present both novel ways of interacting with the environment and have interesting control challenges. Drones that can fold to reduce their size can fit through environmental obstacles that are otherwise impassable, e.g. with actuated arms (53) or with unactuated, folding hinges (54). In, e.g. (56), a quadcopter's four arms are connected to the central body using springs, allowing the system to bend in response to collisions with the environment, recovering more quickly and potentially avoiding catastrophic failure. Another paper looking at surviving/exploiting collisions is (57), where a quadcopter is encased in a tensegrity shell allowing it to survive high speed collisions, relying on the property of tensegrity structures to avoid bending stress (which is typically the cause of failures during a collision). The design of (58) instead encapsulates the four rotors of a quadcopter in passively rotating shells, allowing the drone's extremities to roll off the environment.

Adjusting a vehicle's center of mass, while keeping the propeller thrusts constant, also produces resultant torque on the vehicle, which can be used to change the vehicle orientation. Unlike the simple dynamics of Section 2, in this case the system mass moment of inertia will dynamically change, leading to much more complex dynamics equations. In (59) a quadcopter is presented that can move the location of the payload by sliding the propellers' arms past the central body; in (52) the payload is mounted on a two degree-of-freedom tilting mount on the central body. In both cases, the additional input degrees of freedom can be used for fault-tolerant control in the event of a motor failure.

An extreme example of reducing the energy consumption of a battery-powered quadcopter is given in (12), where a quadcopter is equipped with a staged energy source. Specifically, it is shown how a vehicle's flight time can be increased by ejecting parts of the

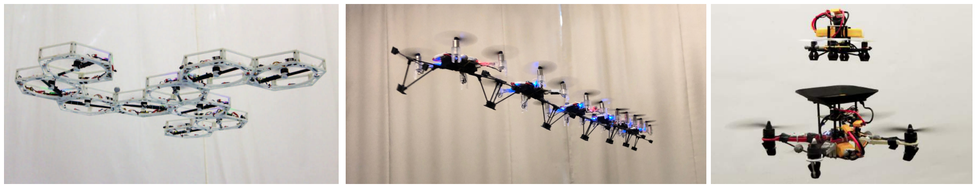

Figure 6

Combining multiple drones potentially enables new capabilities. From left to right (images taken from respective citations): the Distributed Flight Array (67), the ModQuad (68), and the Flying Batteries of (69).

battery as they are depleted, meaning that the vehicle weight reduces as the flight continues – it is noted moreover that the environmental impact rules this out in most practical circumstances.

To overcome the limitations of the battery-based power system, drones may be equipped with gasoline engines or fuel cells (e.g. (60, 61)). Since their specific energy is significantly higher than that of a battery, significantly longer flight times can be achieved. However, the added complexity, shift of the center of mass position due to fuel consumption, the difficulty of controlling a system with sloshing liquid fuel, and the change in mass properties are potential disadvantages compared to battery-electric systems.

5.2. Winged vehicles

The typically larger surface area of a fixed wing has the most potential to reduce the energy consumption of a drone, especially when operating at larger speeds. Hybrid vehicles, that combine the ability to takeoff vertically like a multicopter (with a large wing that can produce lift at speed) promise the best of all worlds, but are typically challenging to control at low speeds in the face of external disturbances, and in the transition stages to/from fixed-wing flight due to complex aerodynamics. Pure fixed-wing aircraft require more space for takeoff and landing, but are mechanically simpler than hybrid vehicles.

A recent example of a hybrid vehicle is given in (62), which presents an annular wing encasing a quadrotor configuration; this configuration has the advantage of also shrouding the propellers and makes the vehicle safer for operation e.g. near humans. Anomaly detection for a hybrid design is presented in (63), where an unsupervised learning approach is applied to data from over 5000 flight missions, avoiding the need for hand-crafted fault detection. The control of fixed-wing aircraft outside nominal aerodynamic conditions remains challenging. In (64) a nonlinear MPC controller is presented for post-stall maneuvers for a fixed-wing drone, allowing for e.g. turns around extermely small radii. The flight envelope of a drone is estimated in (65), to be approximated as a convex space and used in an MPC controller. Where a fixed-wing aircraft has enough thrust to overcome its weight, a tailsitter configuration offers the simple design of a fixed wing aircraft, which can also vertically take off and land; an example of such a vehicle and its control is given in (66).

5.3. Vehicle teams

Having multiple vehicles cooperatively solve a task is often attractive: for example, teams combining drones with ground-based robots can exploit the energy efficiency of ground-based locomotion, while having the greater perspective afforded by the flying vehicle – some recent examples are shown in Figure 6. A particularly exciting instance of this is the Ingenuity drone accompanying the Perseverence rover on Mars (70): a 1.8kg helicopter equipped with two counter-rotating, concentric rotors. Ingenuity is capable of autonomous flights, and will inform the design of future extra-planetary drones. Similarly, in (71), a motion planning strategy is presented for an (earth-based) system comprising both drones and ground vehicles, a motion planner is presented by treating it as a partially observable Markov decision process. Ground-based, mobile recharging robots are combined with drones in (72), specifically focusing on multiple UAVs searching for a target, with the ground-based charging robots constrained a road network. Vehicles that can exploit public transport to cover part of their travel distance are considered in (73), where the specific planning problem is to minimize the maximum time to complete a delivery. The problem of landing a drone on a moving platform is investigated in (74), which specifically considers the effect of communication delays.

Interacting with another aerial vehicle is more challenging than interacting with a ground-based system, but enables a variety of interesting applications. When combining multiple drones, the maximum payload is increased – this is exploited in e.g. (75) to carry a flexible hose for firefighting applications, while (76) presents a distributed MPC controller for collaborative transport using drones.

The concept of multiple modular drones with identical geometrical shapes that can self-assemble in midair is also an interesting topic (77, 67, 78, 79, 80, 68). A system of hexagonal units, each equipped with a single propeller, is presented in (77), with the system relying on assembly on the ground before flight. In (78), four cuboid modular drone robots are assembled to act as "Flying gripper", which can surround objects and carry payloads. A mid-air self-assembly algorithm is introduced in (79) and (80), which can rearrange the module's shape according to its mission. The concept is further evolved in (68), with added degrees of freedom roll motion between joined modules, allowing the thrust of each vehicle to participate in generating a high level of yaw control torques.

The limited flight time and range of drones motivates the ability to transfer a payload from one drone to another, allowing the payload to cover a distance that the individual drone could not achieve in a single flight, as proposed in (81). This requires highly precise control and estimation, with (81) presenting a solution relying only on onboard sensors. An alternative approach to overcoming the energy constraints of drones is given in (69), where a main quadcopter is repeatedly visited by smaller "flying batteries". The main quadcopter can thereby stay aloft much longer, with the flying batteries effectively consisting of a large battery attached to a small quadcopter.

6. Outlook

In this paper we have reviewed some recent publications on the design and control of drones. We note that this remains a vibrant area of research, with dedicated conference sessions and workshops, and that is also able to fascinate the broader public. Turn-key localization solutions like USB-connected tracking cameras make autonomous operations easier than ever, and ever more powerful embedded computers allow for complex computations on small hardware.

A trend in common with robotics more broadly is the increasing use of neural networks and learning-based control. This is especially attractive in situations where gathering firstprinciple models is difficult; but such approaches make it difficult to generate rigorous safety guarantees, which are otherwise typical of aerospace applications. Thus, an important aspect of future work is the creation of safe, learning-enabled control that retains the high-performance capabilities of the vehicles. An example of such work is (82).

For both low-level stabilization and higher-level motion planning, a topic of particular relevance is a tight coupling between the sensors (and their limitations) and the control/actuation. The generation of dynamic trajectories on constrained computational hardware remains an interesting challenge.

Although the first quadcopter designs are now a century old, novel sensors, actuators, control strategies, and missions keep providing for new vehicle designs. Of particular interest at the moment is the use of drones for passenger transport, which has the potential to have a great impact on everyday life. This causes a need for designs that are compact, quiet, efficient, and above all else, safe.

Finally, improvements in battery technology and component efficiency will continue to expand the range and endurance of drones. Nonetheless, the fundamental requirement to operate as economically as possible will continue to be an impetus for more efficient designs, and control.

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