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Design and Control of Drones

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Abstract

The design and control of drones remain areas of active research, and here we review recent progress in this field. In this article, we discuss the design objectives and related physical scaling laws, focusing on energy consumption, agility and speed, and survivability and robustness. We divide the control of such vehicles 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 consider the effects of multivehicle teams.

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 and from 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 with 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, which makes all designs highly integrated and requires economy of both actuators and sensors; and (*c*) severe energy consumption constraints.

In this article, 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 speeds are 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 with more conventional aeronautical designs such as helicopters and fixed-wing aircraft, because of their extremely low mechanical complexity (in the case of a quadcopter, having only four moving parts, which are 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 it 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*a***, although the lack of passive stability meant that modern electronics were required to make them successful (e.g., **Figure 1*b***).

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, which is done through a combination of energy storage and efficiency. We describe some fundamental physical characteristics that capture, to a first approximation, the main trade-offs and limitations for drones. We

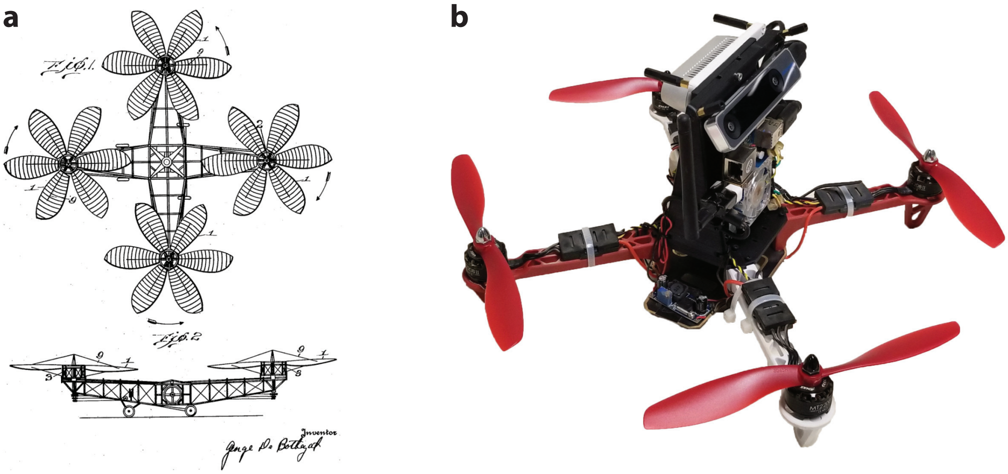

Figure 1

(*a*) A patent drawing from de Bothezat's 1924 patent. Panel adapted from Reference 3. (*b*) A typical custom-assembled research quadcopter, as used in Reference 4.

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 emphasize strategies that explicitly take sensors into account, allowing for reasoning about, e.g., the effect of control actions on uncertainty. Finally, we describe typical vehicle design morphologies, focusing mainly on multicopters but also briefly touching on 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 blades, though propellers with three or more blades are also possible. A higher number of blades typically allows for greater thrust at the same rotational speed, but the relationship to power consumption, noise levels, vibration, and so on 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. **Figure 2** shows diagrams 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 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.

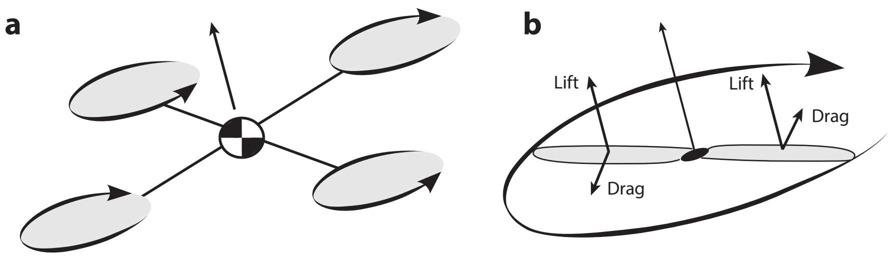

Figure 2

(*a*) A typical multicopter with four propellers, sharing a common thrust direction indicated by the arrow. (*b*) A propeller with two blades. 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 rotor blades' drag force couple).

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 with 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 the models of Faessler et al. (6), used for high-precision control in agile flight, or those of Gill & D'Andrea (7), used 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 counterclockwise 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 produces 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 operation, 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 with 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 hovering 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, Reference 10.

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

2.2. Design Objectives and Scaling Laws

Here, 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, and survivability and robustness. As is typical of aerospace applications, drone designs are highly integrated and typically represent a compromise among 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, a primary objective is range. For a fixed energy storage technology, both flight time and range 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 is 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 expected to have better flight endurance. Similarly, a vehicle that requires lower thrust (e.g., due to lower overall mass) will also have better endurance. The power required grows superlinearly with increasing thrust, which 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 only linearly in the mass used for energy storage.

2.2.2. Agility and speed. In applications such as drone racing (see, e.g., 13–15), 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 equal, the maximum horizontal speed of a vehicle can be increased by reducing its mass, increasing the available 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's 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 the radius and the 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 close 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 endurance and agility is shown schematically in **Figure 3**.

We briefly recapitulate the scaling argument of Kushleyev et al. (16) to investigate the agility of vehicles as the sizes of all components are varied. Such an analysis requires assumptions about how

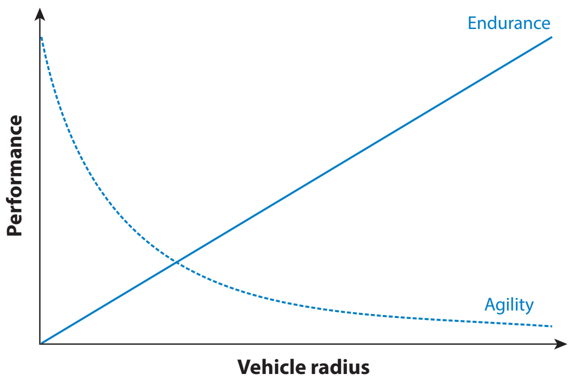

Figure 3

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

the achievable thrust force scales with rotor size—a difficult task, especially because the scaling of the motor and batteries is typically difficult to capture simply. Kushleyev et al. (16) gave two different approximations relating propeller aerodynamic scaling, one 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 other 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 sets of assumptions lead to the conclusion that a multicopter's linear acceleration either is independent of scale or scales proportionally to the vehicle's linear scale. The angular acceleration, however, scales inversely proportional to either 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 able to continue its mission with minimal interruption, which permits simpler control strategies, less precise sensors, and so on. 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 in **Figure 4*a***, where a trajectory planner generates reference states to be tracked by a low-level controller that generates 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 each component to be designed in relative isolation, reducing both design complexity and computational cost and potentially allowing for simpler arguments with respect to optimality. However, as increasing computational power becomes available, tighter integration of components allows a designer to achieve more complex performance specifications (especially with respect to robustness and operation in complex environments).

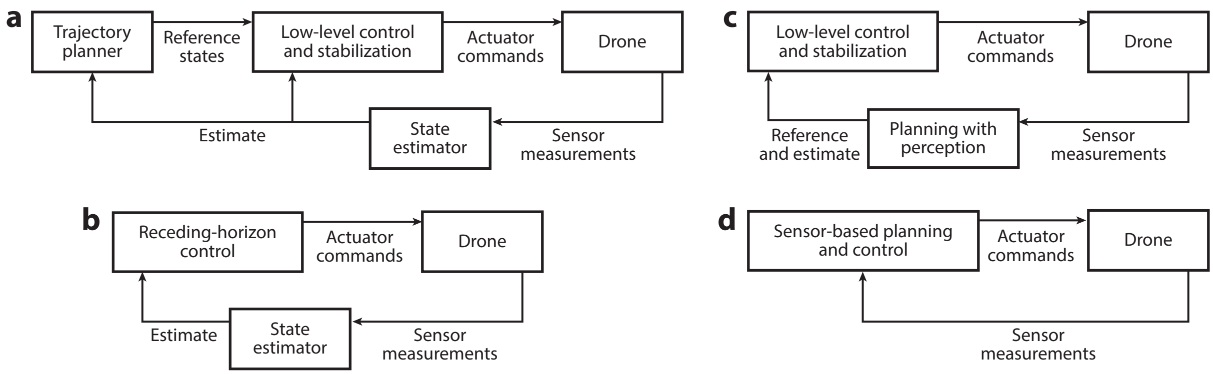

Figure 4

Various control system architectures.

A first step in this direction is the use of receding-horizon control (as shown in **Figure 4*b***), 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. This is shown in **Figure 4*c***.

The final step, as shown in **Figure 4*d***, 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; 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. As shown by the discussion in Section 2, 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 or quaternions (e.g., 17), the rotation matrix itself (e.g., 18), and rotation vectors (e.g., 19). In a first-order analysis, all approaches typically yield similar results, with differences becoming apparent only when recovering from large disturbances or orientation changes.

As these systems are pushed to operate in 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 focuses on accounting for greater errors in state estimation. In situations where accurate modeling is difficult, controllers that learn (either in advance or by adapting 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. Yel & Bezzo (20) used Gaussian processes to approximate system dynamics, with the adaptation occurring only if the model error exceeds a threshold. Adaptive control provides another set of tools to approach such systems; Sankaranarayanan et al. (21) used an adaptive control approach based on Lyapunov analysis 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 uncertainties) and unknown external disturbances (such as wind or gusts). A recent example is a paper by Dhadekar et al. (22) in which 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 a 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, Jarin-Lipschitz et al. (23) designed a robust controller for a multicopter that used visual inertial odometry for state estimation and showed that this controller provided 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, it is important to identify the wind field around the drone and suitably compensate for it. Patrikar et al. (24) equipped a quadcopter with an onboard wind sensor to estimate wind fields in an urban environment. Similarly, Tagliabue et al. (25) designed a quadcopter with additional sensors to estimate the local wind vector, the drag force on the vehicle, and external forces (e.g., due to collisions).

Rather than using models, one can deploy deep reinforcement learning by relying on extensive data. For example, Fei et al. (26) used this approach to react to cyber-physical 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 has been well studied (for a recent review, see, e.g., 27). 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, computational efficiency remains an area of emphasis. 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 also be considered, such as privacy (e.g., 28) and 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 described in Reference 29; more recent works include References 30–33. The primary sensor is typically a vision sensor, with the motion planner attempting to keep particular visual features inside the camera's field of view as the vehicle maneuvers (29, 31, 32) or maneuvering the vehicle to avoid areas with little visual texture, where a visual inertial odometry 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 References 34–36; in References 34 and 35, multiple drones carried out inspections of large structures, using heuristics and a greedy strategy, respectively, to make the problem computationally tractable. The approach in Reference 36 utilized a top-down view of the scene to be captured, creating a coarse model of the scene to generate paths.

Exploring (and generating models or maps of) completely unknown environments represents another difficult challenge. Motivated by the challenge of exploring underground environments such as caves, Reinhart et al. (37) presented an imitation learning approach built from a graph-based planner. The approach aimed to move the drone so that an onboard depth sensor incrementally revealed the environment.

4.2. Collision Avoidance

For most drones, any type of collision is associated with a very high likelihood of crashing and mission failure. 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 an attractive sensor for motion planning applications, as they are relatively lightweight and inexpensive and directly provide 3D information on the environment. Bucki et al. (4) presented a planning approach for a multicopter using a depth camera. Each frame of the depth camera was treated as a local map, through which collision-free trajectories were planned, and the plan was updated with each new depth frame in a receding-horizon fashion. To achieve sufficiently fast computation, this approach specifically exploited the rectangular image of the depth sensor and represented the free space using collision-free pyramids. Yadav & Tanner (38) also used a depth camera, projecting rays 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; References 39 and 40 are two recent examples. Because the motions are precomputed, these methods may be faster to execute than those that rely on real-time computation of motions, but 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. Yu et al. (41) presented an example of a drone equipped with a millimeter wave radar combined with a monocular sensor to track obstacles using an extended Kalman filter, which was followed by motion planning using RRT*, the asymptotically optimal version of the rapidly exploring random tree algorithm (42).

Event cameras, which record changes in the image (rather than the image itself) also hold much promise for dealing with dynamic environments. Sanket et al. (43) combined an event camera with a deep neural network to enable a drone to dynamically avoid obstacles thrown at it, and Falanga et al. (44) introduced an event camera–based high-speed dynamic object extraction technique that enabled a drone to rapidly dodge incoming objects.

The availability of external sensing (such as motion capture) significantly simplifies planning with dynamic obstacles. 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, the approaches used by both Bucki & Mueller (45) and Lindqvist et al. (46) allowed a multicopter to avoid obstacles thrown at it from a short range.

4.3. Energy-Focused Planning

Given the importance of efficiently using the limited energy of a drone, significant efforts have been made 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. Theile et al. (47) used an end-to-end reinforcement learning approach to plan to maximize coverage of an area for a given power budget, and Wu & Mueller (48) used 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, Won (49) combined the placement of static battery-charging stations with trajectory generation for aerial robotics.

5. VEHICLE MORPHOLOGIES

Rapid prototyping tools such as 3D printing facilitate experimentation with different vehicle morphologies, and a wide 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's center of mass; the simplest design capable of hovering is a quadcopter, as shown in **Figure 2*a***. 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. **Figure 5** shows some examples of unconventional multicopters.

Allowing the propeller thrust vector to rotate relative to the vehicle body enables the system to be fully actuated and capable of moving independently of its orientation. Zheng et al. (50) presented a quadcopter with motors mounted on spherical joints (**Figure 5*a***), so that the system can orient the four thrust vectors independently. Similarly, Pose et al. (55) presented a hexacopter with tilted rotors; here, the focus was on the vehicle's ability to maintain stable flight in the face of an actuator failure. Brescianini & D'Andrea (51) presented an approximately rotationally invariant multirotor (**Figure 5*b***), where the vehicle's eight propellers allowed for ominidirectional thrusts and torques, fully decoupling translational from rotational motion.

Vehicles that can change their shape midflight present both novel ways of interacting with the environment and 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)

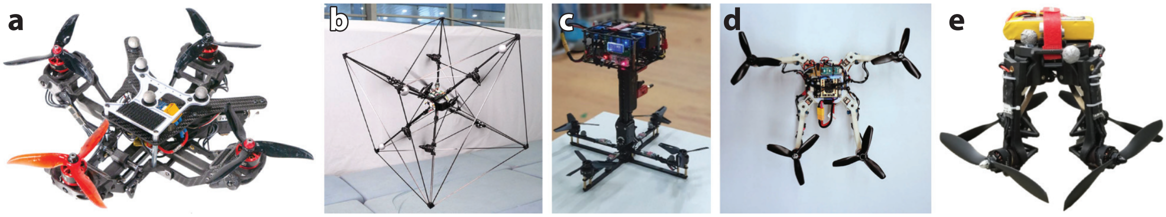

Figure 5

Various unconventional multicopter designs. (*a*,*b*) The TiltDrone (panel *a*), which has motors on spherical joints, and an omnidirectional multirotor vehicle equipped with eight motors (panel *b*). Both of these drones are capable of fully actuated flight. (*c*) The T^3-multirotor. This drone can shift its center of mass by tilting the top platform, enabling it to maintain flight after the failure of a motor. (*d*,*e*) Two shape-shifting drones: a foldable drone with actuated arms that move in the rotor plane (panel *d*) and a passively morphing drone with no actuators beyond the four motors of a conventional quadcopter (panel *e*). Panel *a* adapted from Reference 50 under a CC BY license (**https://creativecommons.org/licenses/by/4.0**); panels *b*–*e* adapted with permission from References 51–54, respectively.

(**Figure 5*d***) or with unactuated, folding hinges (54) (**Figure 5*e***). Patnaik et al. (56) connected a quadcopter's four arms to the central body using springs, which allowed the system to bend in response to collisions with the environment and thereby recover more quickly and potentially avoid catastrophic failure. Zha et al. (57) also looked at surviving or exploiting collisions; encasing a quadcopter in a tensegrity shell allowed 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). Salaan et al. (58) instead encapsulated 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 torque on the vehicle, which can be used to change the vehicle's 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. Kumar et al. (59) presented a quadcopter that can move the location of the payload by sliding the propellers' arms past the central body, and Lee et al. (52) mounted the payload on a two-degree-of-freedom tilting mount on the central body (**Figure 5*c***). In both cases, the additional input degrees of freedom can be used for fault-tolerant control in the event of a motor failure.

Jain et al. (12) provided an extreme example of reducing the energy consumption of a battery-powered quadcopter, equipping the vehicle with a staged energy source. Specifically, they showed how a vehicle's flight time can be increased by ejecting parts of the battery as they are depleted, meaning that the vehicle's weight decreases as the flight continues. However, the environmental impact rules out this approach in most practical circumstances.

To overcome the limitations of battery-based power systems, 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, these energy sources can enable significantly longer flight times. However, the added complexity, shift in the position of the center of mass as fuel is consumed, difficulty of controlling a system with sloshing liquid fuel, and change in mass properties are potential disadvantages compared with systems that use electric batteries.

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, which combine the ability to take off vertically like a multicopter with a large wing that can produce lift at speed, promise the best of all worlds, but they are typically challenging to control at low speeds in the face of external disturbances and in the transition stages to and from fixed-wing flight due to the complex aerodynamics. Pure fixed-wing aircraft require more space for takeoff and landing but are mechanically simpler than hybrid vehicles.

Gill & D'Andrea (62) provided a recent example of a hybrid vehicle, presenting 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. Sindhwani et al. (63) presented anomaly detection for a hybrid design, applying an unsupervised learning approach to data from more than 5,000 flight missions and avoiding the need for hand-crafted fault detection.

The control of fixed-wing aircraft outside nominal aerodynamic conditions remains challenging. Basescu & Moore (64) presented a nonlinear model predictive controller for poststall maneuvers by a fixed-wing drone, allowing for, e.g., turns around extremely small radii. Zogopoulos-Papaliakos & Kyriakopoulos (65) estimated the flight envelope of a drone by approximating it as a convex space and using a model predictive controller. Where a fixed-wing aircraft has enough thrust to overcome its weight, a tail-sitter configuration offers the simple design of a fixed-wing

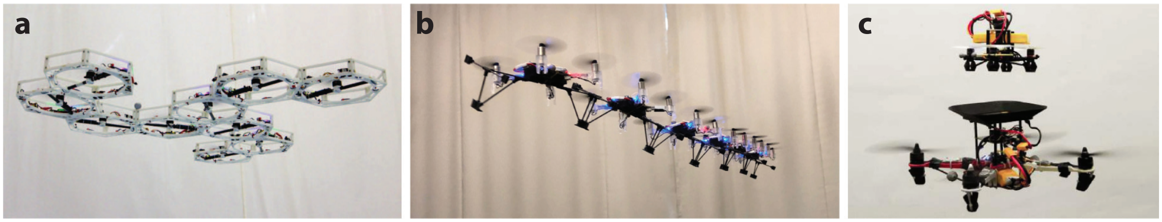

Figure 6

Combining multiple drones to potentially enable new capabilities: (*a*) the Distributed Flight Array, (*b*) the ModQuad, and (*c*) flying batteries. Panels *a*–*c* adapted with permission from References 67–69, respectively.

aircraft that can also vertically take off and land; Ritz & D'Andrea (66) presented an example of such a vehicle and its control.

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 is the Ingenuity drone accompanying the Perseverance rover on Mars (70). A 1.8-kg helicopter equipped with two counterrotating, concentric rotors, Ingenuity is capable of autonomous flights and will inform the design of future extraplanetary drones. Similarly, Chen et al. (71) presented a motion planning strategy for an (Earth-based) system comprising both drones and ground vehicles that treats the planner as a partially observable Markov decision process. Booth et al. (72) combined ground-based, mobile recharging robots with drones, specifically focusing on multiple drones searching for a target, with the ground-based charging robots constrained by a road network. Choudhury et al. (73) considered vehicles that can exploit public transport to cover part of their travel distance, where the specific planning problem is to minimize the maximum time to complete a delivery. Muskardin et al. (74) investigated the problem of landing a drone on a moving platform, specifically considering 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. Combining multiple drones increases the maximum payload, which has been exploited by, e.g., Kotaru & Sreenath (75) to carry a flexible hose for firefighting applications. Wehbeh et al. (76) presented a distributed model predictive controller for collaborative transport using drones.

The concept of multiple modular drones with identical geometrical shapes that can self-assemble in midair is also interesting (67, 68, 77–80). Oung & D'Andrea (77) presented a system of hexagonal units, each equipped with a single propeller, with the system relying on assembly on the ground before flight. Gabrich et al. (78) assembled four cuboid modular drone robots to act as a flying gripper that can surround objects and carry payloads. Saldana et al. (79) and Li et al. (80) introduced a midair self-assembly algorithm that can rearrange the module's shape according to its mission. Gabrich et al. (68) further developed this concept by adding degrees of freedom to the roll motion between joined modules, allowing the thrust of each vehicle to participate in generating a high level of yaw control torques (**Figure 6*b***).

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 an individual drone could not achieve in a single flight, as proposed by Shankar et al. (81). This requires highly precise control and estimation, and the authors presented a solution that relied only on onboard sensors. Jain & Mueller (69) described an alternative approach to overcoming the energy constraints of drones, where a main quadcopter is repeatedly visited by smaller flying batteries (**Figure 6*c***). 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 article, we have reviewed some recent publications on the design and control of drones. These remain vibrant areas of research, with dedicated conference sessions and workshops, and are also able to fascinate the broader public. Turnkey localization solutions such as 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 first-principle models is difficult; however, such approaches make it difficult to generate rigorous safety guarantees, which are otherwise typical of aerospace applications. Thus, an important aspect of future work will be the creation of safe, learning-enabled control that retains the high-performance capabilities of the vehicles. Reference 82 is an example of such work.

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 or 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 continue to inspire new vehicle designs. Of particular interest at the moment is the use of drones for passenger transport, which could potentially have a great impact on everyday life. This use leads to 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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