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State-of-the-Art in Successive Convexification for Trajectory Optimization

Introduction and Background

Successive Convexification (often abbreviated **SCvx**) is an advanced optimization methodology for solving challenging non-convex trajectory planning problems by *iteratively* solving a series of convex sub-problems. It originated in the context of space vehicle guidance and control, where problems like planetary landing or spacecraft maneuvering involve complex nonlinear dynamics and constraints. Traditional trajectory optimization methods either relied on simplified analytic guidance laws or on direct nonlinear programming, but these approaches had limitations (e.g. inability to handle complex constraints, or requiring too much onboard computation) [1] [2]. Convex optimization techniques, by contrast, offer deterministic convergence and polynomial-time solvability, but applying them directly requires the problem to be convex. *Successive convexification* bridges this gap by converting a non-convex optimal control problem into a sequence of convex problems, each one a convexified approximation of the original, and iteratively refining the solution. This technique was first introduced for rocket landing guidance problems around 2016–2018 and has since been recognized as a new paradigm in real-time trajectory optimization [3].

Notably, NASA and other institutions have invested significant research into SCvx for guidance and control. The seminal work by Michael Szmuk and Behçet Açıkmeşe in 2017–2018 demonstrated SCvx on a six-degrees-of-freedom (6-DoF) Mars powered descent problem. They showed that iteratively solving convex sub-problems can reliably handle the complex nonlinear dynamics of a rocket with thrust and attitude constraints, even allowing the final landing time to be free (optimized) rather than fixed. This opened the door to high-fidelity, real-time capable guidance algorithms for planetary landers, reusable launch vehicles, and other aerospace trajectory challenges. In the years since, numerous extensions and applications have been explored in academia, NASA centers, and industry, confirming SCvx as a state-of-the-art method in optimal guidance. NASA's interest is evident: for example, researchers at NASA Langley have noted that *"successive convexification (SCvx) has gained much attention for trajectory optimization"* in recent years [4]. Even outside of NASA, major aerospace companies have embraced convex-optimization-based guidance – SpaceX reportedly employs high-speed onboard convex solvers for Falcon 9 booster landings [5], and Blue Origin and Astrobotic are investigating related convex guidance approaches for lunar landers [5]. These developments underscore the importance of SCvx in both research and real-world aerospace applications.

Fundamental Principles of Successive Convexification

At its core, successive convexification is a form of **Sequential Convex Programming (SCP)** tailored for optimal control problems. The fundamental idea is to start from an initial reference trajectory (which need not be dynamically feasible) and then repeatedly **linearize** the nonlinear dynamics and **convexify** any non-convex constraints around the current trajectory, solving a convex optimization at each iteration. Each convex sub-problem produces an improved trajectory, which serves as the reference for the next iteration. This process continues until convergence, at which point the solution is taken as an (approximate) optimum of the original non-convex problem. In essence, the method "transforms the non-convex problem into a sequence of convex optimization problems that are solved in succession to convergence". By leveraging powerful interior-point solvers for each convex sub-problem, SCvx can find high-quality solutions efficiently and reliably, even for problems that are otherwise intractable in real time.

A critical component of SCvx is ensuring *feasibility* and *convergence* despite the approximations made at each step. This is typically achieved through the introduction of **trust regions** or **slack variables** (sometimes called *virtual controls*). In practice, the linearized dynamics are augmented with small fictitious control terms (e.g. a "synthetic acceleration" term) that act as buffers between the current linear approximation and the true nonlinear system [6] [7]. These slack terms allow the convex sub-problems to remain feasible (so the solver always finds a solution), even if the current reference trajectory is far from valid. Importantly, the algorithm penalizes any use of these synthetic controls in the cost function, so that across iterations the solution "drives" the slack terms to zero [8] [9]. In the final converged solution, the artificial control is zero (or negligibly small), meaning the trajectory exactly satisfies the original nonlinear dynamics and constraints. This approach ensures that *each iteration yields a feasible trajectory for the convexified problem while the final solution satisfies the true dynamics*. In addition, SCvx formulations impose trust-region bounds on how much the solution is allowed to change between iterations (the trust-region radius shrinks if the linearization was poor), which helps maintain the validity of the linear approximation [10] [11]. The combination of these strategies guarantees that the iterative process is stable and converges to a physically valid trajectory, albeit generally to a **locally** optimal solution (global optimality is not guaranteed for arbitrary non-convex problems, though each convex sub-problem is solved to global optimality within its approximation).

Another key aspect of successive convexification is the handling of **non-convex constraints** such as thrust bounds, pointing limitations, or obstacle avoidance. Earlier convexification methods often required specific tricks to handle such constraints (for example, the *lossless convexification* approach converts a non-convex thrust constraint into a convex one by allowing thrust to momentarily go to zero with a clever reformulation). SCvx, by contrast, can treat a much broader class of constraints by iteratively approximating them. For instance, attitude constraints (like a maximum tilt angle for a lander) or a **"glideslope"** requirement (keeping the vehicle above a certain approach angle) are originally non-convex, but in SCvx they can be imposed as convex constraints after appropriate convexification or conservative linearization at each iteration. If a constraint is state-triggered or otherwise nonlinear, modern SCvx implementations use techniques like **dual quaternions** or **logic constraints** to convexify them piecewise or include them via penalty methods. Overall, the methodology ensures that all mission constraints (e.g. thrust limits, tilt limits, no-fly zones, line-of-sight constraints, etc.) are explicitly enforced at every iteration in a convex form, thus guaranteeing that the final trajectory respects all original requirements by construction [12] [13]. This ability to handle complex constraints while maintaining dynamic feasibility is a major advantage of successive convexification over traditional open-loop guidance algorithms.

To summarize the SCvx algorithm in simple steps:

1. **Initialize with a reference** (guess) trajectory, which can be *dynamically inconsistent* (not exactly following the dynamics). Often a crude guess like a straight-line or gravity-turn path is used just to have something to start with.
2. **Convexify the problem around the current trajectory:** Linearize the equations of motion about the reference trajectory (producing a linear time-varying model) and convexify any non-linear constraints (using approximations or slack variables). This yields a convex optimization problem (commonly a Second-Order Cone Program, SOCP) that is an approximation of the original problem in the neighborhood of the reference [14].

3. **Solve the convex sub-problem:** Use a convex solver (interior-point method or similar) to obtain an optimal trajectory for the convexified problem. This can be done very quickly thanks to modern solvers and problem sparsity, often in milliseconds for moderately sized problems.
4. **Update the reference:** The newly obtained trajectory (solution) is now used as the reference for the next iteration.
5. **Repeat:** The process of linearization and solving is repeated, each time hopefully reducing the needed "corrections" (the slack/virtual control usage and trust-region violations shrink). The iterations continue until convergence criteria are met – for example, until the changes in the trajectory or cost between iterations fall below a threshold, and constraint violations are eliminated.
6. **Output final trajectory:** The final solution is a trajectory that is dynamically feasible for the original nonlinear system and (if all goes well) near-optimal with respect to the original cost. In the rocket landing case, this means a guidance command history (throttle and orientation commands over time) that will take the vehicle from its initial state to a precise landing, minimizing fuel or time as specified, while obeying all safety and performance constraints.

Because SCvx solves a sequence of convex problems, it is computationally heavier than a one-shot convexification (like G-FOLD, discussed below) – however, the approach is **much more general**. It can handle free-final-time problems (where the optimal time-of-flight is solved for), state-triggered events, complex dynamics like full 6-DoF rigid-body motion, and even combinatorial aspects (with modifications) in ways that fixed-form convex reforms cannot. Modern enhancements to SCvx have even introduced methods to enforce **continuous-time constraint satisfaction** (so that constraints are obeyed not just at discrete time nodes, but truly continuously) and to provide **convergence guarantees** under certain conditions. These advances draw on techniques such as penalty methods, multiple-shooting discretization, and the *proximal linear* (prox-linear) algorithm from nonlinear optimization theory. In short, successive convexification has matured into a robust framework that combines the reliability of convex optimization with the flexibility needed for real-world, nonlinear trajectory design.

Key Developments in Literature

Since its introduction, successive convexification has been the subject of numerous research papers, technical reports, and implementations. Below we highlight some of the **key publications and milestones** in the development of SCvx, especially those involving NASA, academia, and peer-reviewed venues:

- **Early Foundations (2013–2016):** The concept of iteratively refining trajectories via convex optimization builds on earlier work in *successive approximation* and sequential convex programming. Notably, **J. Casoliva's 2013 PhD thesis** proposed "successive approximation for powered descent and cycler trajectories," laying groundwork for these ideas. Around the same time, researchers like X. Liu and P. Lu demonstrated that certain non-convex optimal control problems (e.g. entry guidance) could be solved by convex optimization with successive linearizations. These precursors introduced the feasibility of convex approaches to traditionally non-convex guidance problems.

- **Lossless Convexification Era (2014–2015):** Before SCvx was fully formulated, a significant breakthrough was **lossless convexification**. *Blackmore et al.* and others (2010s) showed that the non-convex thrust constraint in a fixed-time fuel-optimal landing problem could be transformed into a convex constraint without loss of optimality. This led to **G-FOLD (Guidance for Fuel Optimal Large Diverts)**, a convex guidance algorithm for planetary landing that NASA's Jet Propulsion Laboratory flight-tested successfully on a subscale rocket lander in 2014. Those flight demonstrations proved that convex optimization could run in real-time onboard a vehicle and meet mission constraints, paving the way for the more general SCvx method. However, lossless convexification was limited to specific problem forms (e.g. fixed final time, thrust bounded away from zero).

- **SCvx Introduction (2016–2018):** The formal introduction of *Successive Convexification* as a generalized method is credited to **Michael Szmuk and Behçet Açıkmeşe** and colleagues. In 2017, they presented SCvx applied to a *Mars 6-DoF rocket landing guidance* problem, initially assuming a fixed final time and focusing on minimum-fuel solutions. This was followed by their 2018 AIAA SciTech paper which extended the method to a *free-final-time, minimum-time landing problem*. According to these seminal papers, SCvx was able to generate dynamically feasible trajectories that satisfy thrust, tilt, and glide-slope constraints for a powered descent, and it could do so fast enough for real-time guidance. The 2018 work in particular demonstrated that even the landing duration could be optimized within the iterative convex framework, a significant advance over prior convex methods which held final time fixed. Together, Szmuk et al.'s 2017–2018 studies introduced the core SCvx algorithm and showed its effectiveness on complex 6-DoF lander models [3]. These papers are widely cited as the beginning of the SCvx literature and "introduced a new paradigm in the field of real-time trajectory optimization" [3].

- **Rotational Dynamics and Attitude Constraints (2019–2021):** After the initial formulation, researchers worked to incorporate more sophisticated attitude representations and constraints into SCvx. **Reynolds, Szmuk, Açıkmeşe et al.** developed a dual-quaternion based 6-DoF SCvx guidance that could handle *state-triggered constraints* (like keeping certain angles or line-of-sight conditions until specific events). This work was published in *Journal of Guidance, Control, and Dynamics (JGCD) 2020*. Around the same time, **Padraig Lysandrou and Robert Braun (2021)** implemented a 6-DoF SCvx guidance using *Modified Rodrigues Parameters (MRPs)* for attitude, simplifying some quaternion complexities. These advances allowed SCvx to better handle complex attitude dynamics (e.g., avoiding gimbal lock, integrating line-of-sight keeps outs, etc.) while retaining convex solvability. The continuing refinement of SCvx in this period also addressed issues like variable vehicle mass distribution and more robust trust-region strategies, as evidenced by ongoing publications.

- **New Applications – Rendezvous, Entry, and Beyond (2020–2022):** Researchers did not limit SCvx to landing problems. For example, **Dmytro Malyuta, Tyge Reynolds, and colleagues (2020)** applied SCvx to spacecraft rendezvous and docking scenarios, including difficult constraints like on/off (integer) thrusters and collision avoidance. They showed that successive convexification could plan fuel-efficient rendezvous trajectories, even incorporating discrete decisions (via an outer loop or heuristic) for thruster on/off scheduling. Another application was planetary *aerodynamic entry guidance*: a study by **Uzun, Açıkmeşe, Carson, etc. (2023)** extended SCvx to the hypersonic entry phase of Mars EDL (Entry, Descent, Landing), using compound state-triggered constraints to respect heating and g-load limits during atmospheric flight [15] [16]. On a different front, a team from NASA JPL and TU Delft (Mazouz, Quadrelli, Mooij, 2021) demonstrated SCvx for **precision landing on Titan**, Saturn's moon, showing the method's adaptability to scenarios with atmospheric descent and different gravity. SCvx has even been explored for non-aerospace problems like UAV maneuvering and autonomous driving. For instance, researchers used SCvx for minimum-time 6-DoF trajectory optimization of quadrotor drones and for motion planning in self-driving cars [17] – underscoring the technique's broad applicability.

- **Consolidation and Tutorials (2022):** By 2022, the body of work on successive convexification had grown large enough that survey and tutorial articles appeared. A notable example is the **IEEE Control Systems Magazine tutorial (Oct 2022)** by Malyuta *et al.*, which provides a comprehensive overview of convex optimization techniques for trajectory generation, including SCvx. This tutorial (and similar courses, such as NASA's NESC Academy lectures) compiles best practices from numerous studies, covering how to formulate problems for SCvx, ensure real-time performance, and handle edge cases. The message from these tutorials is clear: SCvx had matured from a nascent idea to a proven approach, with software tools and a community of practitioners growing around it.

- **Recent Advances and Theory (2023–2025):** Current research is pushing the boundaries of SCvx in both theory and practice. In late 2023 and 2024, Açıkmeşe's lab (University of Texas at Austin) published new results on **guaranteed convergence** and improved mathematical foundations for SCvx. For example, **Elango, Kamath, Açıkmeşe et al. (2024)** introduced a *continuous-time successive convexification* framework that uses an exterior penalty for continuous constraints and a prox-linear algorithm to ensure convergence to KKT stationary points of the original problem. This work addresses one known drawback of earlier SCvx implementations – the need for sufficiently fine discretization – by enforcing constraints continuously in time and proving that the discrete solution corresponds to a valid continuous trajectory. On the practical side, NASA researchers **Alex Hayes and Jing Pei (Langley)** presented in 2024 an extension of SCvx to account for *time-varying mass properties* (changes in center of mass and inertia) for large landers like SpaceX's Starship. Their simulations showed that neglecting mass variation can lead to different optimal trajectories, and incorporating it via SCvx yields more accurate guidance for long-duration descents with significant fuel burn-off. Such refinements are crucial as agencies plan for human-class lunar landers and Mars vehicles. We also see SCvx being combined with parallel computing and distributed optimization (to handle swarms of satellites or faster solving) in very recent literature. In summary, the technique is still rapidly evolving, with ongoing research focusing on improving its reliability, efficiency, and range of applicability.

Real-World Implementations and Test Cases

One of the reasons successive convexification garners interest is its potential for **real-time, onboard guidance** in demanding missions. Several notable implementations and test cases illustrate the progress toward deploying SCvx in real systems:

- **NASA's Powered Descent Guidance Simulations:** NASA has been actively testing SCvx within high-fidelity mission simulations. Chadalavada *et al.* (NASA Langley, 2023) integrated a 6-DoF SCvx guidance algorithm into **POST2**, NASA's high-fidelity flight mechanics simulation tool used for Mars EDL analysis [18] [19]. They demonstrated SCvx generating guidance for both the terminal powered descent phase and even the hypersonic entry phase of a human Mars landing, all within the full flight simulation loop. A key result was that SCvx could run fast enough to be called *in real time* during the simulation, thanks to its efficient convex solves and the use of modern onboard computing assumptions [13] [20]. This work also leveraged a **Julia-based SCvx toolbox from the University of Washington** as the solver engine, showing collaboration between NASA and academia on the software side [21] [22]. The outcome is promising: SCvx-based guidance was able to meet tight landing accuracy requirements (on the order of meters) while respecting constraints like glide-slope, tilt, heat load, and g-load, all in a realistic simulation of a Mars landing [23] [4]. This is a strong step toward eventual *onboard use* of SCvx in missions.

- **Flight Demonstrations of Convex Guidance:** While, to date, **SCvx itself** has not yet been flight-tested on an actual spacecraft or rocket (as of 2025), its immediate predecessor **G-FOLD was demonstrated in flight**. NASA JPL and Masten Space Systems collaborated in 2014 to test a fuel-optimal convex guidance law (using lossless convexification) on the Masten **Xombie** rocket, achieving accurate pin-point landings under automatic control. The success of those tests provided confidence that solving optimization problems onboard a vehicle is feasible within the timeframe of a real descent. SCvx builds on the same computational principle, but with more generality. Given the simulation results and increasing computational power, it's anticipated that SCvx will be used in upcoming flight experiments or missions. For example, NASA's **SPLICE** program (Safe and Precise Landing – Integrated Capabilities Evolution) has been researching advanced GN&C for lunar landings, and dual-quaternion SCvx guidance was developed under that program for potential use in future lunar lander projects [12]. Moreover, SpaceX's achievement of autonomous booster landings suggests that some form of successive convex optimization is already flying; in fact, SpaceX has "relied on high-speed onboard convex optimization algorithms" for Falcon 9 since the mid-2010s [5]. Although details are proprietary, this likely includes iterative optimization for trajectory shaping during descent (comparable to SCvx in spirit). Blue Origin, planning lunar landing missions (Blue Moon lander), has also been looking at SCvx-related methods (like lossless convexification combined with 6-DoF guidance) for its descent guidance system [24]. These industry uses can be seen as real-world validations of the core idea behind SCvx – optimize trajectories online, satisfy constraints, and react to dispersions – even if the specific algorithms may differ slightly.

- **Technology Transfer and Collaborations:** The development of successive convexification has been a collaborative effort between academia, NASA, and industry. A prime example is the partnership between **University of Washington's Autonomous Control Lab** (led by Açıkmeşe) and NASA centers. Many of the foundational SCvx papers were co-authored by university researchers and NASA engineers together. For instance, the 6-DoF free-final-time SCvx paper was done at University of Washington but addressed a NASA-relevant Mars landing problem. NASA has since funded follow-up research (e.g., through the Space Technology Research Grants program) to extend SCvx and transfer it into practice. The NASA Langley work by Hayes & Pei (2024) on time-varying mass SCvx was done by NASA researchers building on published literature. Additionally, NASA employed contractors (such as Analytical Mechanics Associates) to bring expertise in SCvx for mission analysis, as seen in the Mars EDL simulation integration [25] [18]. On the industry side, there is clear cross-pollination: SpaceX and Blue Origin have hired graduates and experts in convex optimization, and companies like **Astrobotic** (which is developing lunar landers) are known to collaborate with research teams on advanced guidance algorithms [5]. The NASA Technical Memorandum *"MATLAB Implementation of a SCvx Algorithm for 3-DoF Rocket Landings"* (2023) is another form of tech transfer – it serves as a tutorial to help NASA engineers learn and implement SCvx using tools like MATLAB's `coneprog` solver [26] [27]. This document explicitly notes that many aerospace companies are already leveraging convex optimization and that NASA's in-house expertise was limited, hence the need to disseminate this knowledge more widely [5] [28]. Such efforts are enabling a broader community of engineers to adopt SCvx for practical projects.

- **Test Cases in Simulation and Analysis:** Apart from actual flights, SCvx has been tested on a variety of high-consequence scenarios through simulation. These include: **Lunar landing pinpoint guidance** (e.g., large divert maneuvers to avoid hazards while minimizing fuel), **Martian landing with hazard avoidance** (integrating SCvx with onboard vision to re-target safe landing spots, a scenario being studied by NASA and academia), **Spacecraft proximity operations** (such as autonomous rendezvous with a tumbling object or formation flying, tested by groups like Stanford/Caltech with SCvx in the loop), and **Responsive launch vehicle aborts**. For example, a 2021 study from TU Delft used SCvx for optimal on-board abort guidance during launch vehicle ascent, illustrating how the method could plan an emergency return trajectory on the fly [29]. In all these cases, SCvx's ability to handle multiple constraints (keep thrust and angle limits, avoid no-fly zones, meet terminal conditions) while optimizing an objective (minimize time, fuel, or risk) has been proven in silico. Many of these simulations use high-fidelity models and even Monte Carlo trials with dispersions, demonstrating robustness. The results generally show that SCvx can consistently find feasible, near-optimal trajectories where classical guidance laws either fail or are overly conservative [4] [2]. This track record gives confidence that as new missions (like lunar landings under Artemis, Mars Sample Return entries, or advanced spacecraft maneuvers) come up, successive convexification will be a strong candidate in their Guidance, Navigation, and Control (GN&C) toolset.

Conclusion and Outlook

In summary, **Successive Convexification (SCvx)** has emerged as a powerful methodology for trajectory optimization, blending the reliability of convex optimization with iterative refinement to tackle non-convex aerospace problems. Its fundamental principle is to *linearize and resolve* – capturing nonlinear dynamics and constraints through successive convex problems that converge to a feasible solution of the original problem. Over roughly the past decade, a rich body of work has developed around SCvx: from foundational theory and convergence proofs, to numerous application-driven studies in landing rockets, docking spacecraft, planetary entry, UAV flight, and more. The technique has been championed by researchers at top institutions and has drawn the interest of NASA centers and the space industry alike. Key papers by Szmuk, Açıkmeşe, and others introduced the method for rocket descent guidance, and subsequent research has expanded its capabilities (e.g., handling 6-DoF motion, state-triggered constraints, variable vehicle mass). NASA's involvement, through technical reports and simulation integrations, indicates that SCvx is transitioning from research to practice [19] [13]. Indeed, elements of successive convexification are already at work in commercial launch and landing systems (as evidenced by SpaceX's and Blue Origin's use of onboard convex planners) [5], and ongoing collaborations are accelerating the maturation of the technology.

Looking ahead, there are a few trends and challenges that define the state-of-the-art in SCvx. One is the push for **real-time embedded implementation** – ensuring that the iterative convex solver can run within the tight cycle times of flight computers. This has driven research into custom solvers, code generation (e.g. auto-coding the SCvx algorithm in C/C++ for flight processors) [30], and parallelization. Another focus is **certification and reliability**: missions will require guarantees that the SCvx guidance will converge every time and handle off-nominal conditions. The recent theoretical work on convergence guarantees and on enforcing continuous-time feasibility is a step in this direction. Additionally, extending SCvx to cover mixed discrete/continuous problems (such as combining logical decisions with trajectory optimization) is an active area – relevant for hybrid propulsion systems or multi-phase missions. There is also interest in applying SCvx beyond spacecraft: for example, advanced air mobility (drones, air taxis) and robotics, where real-time trajectory re-planning with complex constraints is needed, can benefit from the method's speed and rigor.

In conclusion, successive convexification represents the **state-of-the-art** in optimal trajectory design methodology, particularly in aerospace scenarios with demanding constraints and the need for on-the-fly re-planning. It builds upon and enhances earlier convex optimization approaches, offering a systematic way to handle nonlinearity and nonconvexity without sacrificing the guarantees of convex solvers. The existing body of work – from NASA technical memoranda to AIAA journal papers – provides a strong foundation for SCvx, and real-world tests continue to validate its potential. As both the technology (onboard computing, solver efficiency) and the methodology (theoretical robustness, new applications) advance, we can expect to see successive convexification playing a key role in future high-profile missions, such as lunar landings, Mars exploration, and autonomous space operations. The collaboration between research institutions, space agencies, and industry ensures that this technique is moving rapidly from simulations and papers to hardware and missions, truly embodying a modern success story of controls and optimization research impacting aerospace engineering [5] [28].

References: The information above is drawn from a range of sources, including NASA technical reports and presentations, academic journals, and conference papers. Key references include Szmuk & Açıkmeşe's foundational AIAA SciTech papers on SCvx, follow-up studies in JGCD and AIAA forums extending the method, NASA Langley's research on SCvx for lunar landers, the IEEE Control Systems tutorial on convex trajectory optimization, and the NASA TM on SCvx implementation [5] [31], among others. These and other cited works provide further detail on the SCvx algorithm and its applications.

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