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# Survey of autonomous guidance methods for powered planetary landing

**Key words:** Autonomous guidance methods; Pinpoint soft landing; Powered descent; Nonlinear programming

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# Motivation

- With the increasing demand for reusable launchers and more scientific returns from space exploration, pinpoint soft landing has become a basic requirement.
- The position accuracy of future planetary landers is within tens of meters of a target respecting all constraints of velocity and attitude, and autonomous guidance methods (AGMs) are considered as a key technology to achieve pinpoint landing.
- An AGM considers the flight process as a whole, and has strong adaptability and robustness for tasks consisting of strong environmental uncertainties and strict constraints.

# Main idea

- This paper states the generalized 3- and 6-DoF optimization problems in the powered descent phase and compares the features of three typical scenarios, lunar landing, Mars landing, and rocket recovery.
- Three key issues related to AGM applications, including physical feasibility, model accuracy, and real-time performance, are presented.
- The characteristics and adaptability of AGMs are detailed by comparing the analytical guidance methods, numerical optimization algorithms, and learning-based methods.

# Method

| Method | Characteristics | Algorithms |
|---|---|---|
| Analytical guidance methods | 1) Fast calculation<br>2) Simplified problem | 1) Polynomial guidance<br>2) Maximum principle<br>3) ZEM/ZEV |
| Numerical optimization algorithms | 1) More constraints<br>2) Model-based<br>3) Convergence & computational efficiency need to be improved | 1) Convex optimization<br>2) Other numerical methods such as the homotopy method, sensitivity method, and numerical predictor-corrector method |
| Learning-based methods | 1) Trained off-line and calculated online<br>2) Affected deeply by training samples | 1) Deep neural networks<br>2) Reinforcement learning |

# Major results

- A general powered planetary landing problem is provided.

- Dynamics

$$\begin{cases} \dot{\boldsymbol{r}} = \boldsymbol{v}, \\ \dot{\boldsymbol{v}} = \boldsymbol{F}/m - 2\boldsymbol{\omega}_{\mathrm{p}} \times \boldsymbol{v} - \boldsymbol{\omega}_{\mathrm{p}} \times (\boldsymbol{\omega}_{\mathrm{p}} \times \boldsymbol{r}), \\ \boldsymbol{F} = \boldsymbol{D} + \boldsymbol{T} + \boldsymbol{G}, \\ \dot{m} = -\|\boldsymbol{T}\|/(I_{\mathrm{sp}} g_0), \end{cases}$$

$$\begin{cases} \dot{\boldsymbol{\omega}} = \boldsymbol{J}^{-1} \cdot (\boldsymbol{M} - \boldsymbol{\omega} \times \boldsymbol{J}\boldsymbol{\omega}), \\ \dot{\boldsymbol{q}} = \frac{1}{2}\boldsymbol{\Omega}(\omega) \cdot \boldsymbol{q}, \end{cases}$$

- Performance index

$$J_{\mathrm{MPC}} = \int_{t_0}^{t_f} (\Delta \boldsymbol{X}(t) \boldsymbol{Q} \Delta \boldsymbol{X}(t) + \Delta \boldsymbol{U}(t) \boldsymbol{R} \Delta \boldsymbol{U}(t)) \mathrm{d}t,$$

$$\begin{cases} J_1 = \int_{t_0}^{t_f} -\dot{m}(t)\,\mathrm{d}t, \quad J_2 = -m(t_f), \\ J_3 = \int_{t_0}^{t_f} \|\boldsymbol{T}(t)\|\,\mathrm{d}t, \quad J_4 = t_f, \\ J_5 = \|\boldsymbol{r}(t_f) - \boldsymbol{r}_f\|^2. \end{cases}$$

- Constraints

$$\begin{cases} [\boldsymbol{r}, \boldsymbol{v}](t_0) = [\boldsymbol{r}_0, \boldsymbol{v}_0], \\ m(t_f) \geq m_{\min}, \end{cases}$$

$$\begin{cases} \cos\theta_{\max} \cdot \|\boldsymbol{T}\| \leq T_y, \\ \cos\gamma_{\max} \cdot \|\boldsymbol{r} - \boldsymbol{r}_f\| \leq r_y - r_{yf}, \end{cases}$$

$$\begin{cases} \phi_{\min} \leq \phi \leq \phi_{\max}, \\ \psi_{\min} \leq \psi \leq \psi_{\max}, \\ \omega_{\min} \leq \omega_{\phi,\psi} \leq \omega_{\max}, \end{cases}$$

$$\begin{cases} \|\boldsymbol{r}(t_f) - \boldsymbol{r}_f\| \leq \varepsilon_{\boldsymbol{r}}, \\ \|\boldsymbol{v}(t_f) - \boldsymbol{v}_f\| \leq \varepsilon_{\boldsymbol{v}}, \\ \|\phi(t_f) - \pi/2\| \leq \varepsilon_{\phi}, \end{cases}$$

$$\mathrm{d}m_{\min} \leq \dot{m} \leq \mathrm{d}m_{\max} \Leftrightarrow T_{\min} \leq \|\boldsymbol{T}\| \leq T_{\max}.$$

# Major results

- Comparing the features of three typical scenarios, i.e., the lunar, Mars, and Earth landing.

Lunar
- Negligible aerodynamic force
- Analytical algorithm or direct method of online planning is adopted

Mars
- Uncertain initial conditions
- Online planning (convex optimization) is needed at least once

Earth
- Complex atmospheric environment
- Limited engine throttling range & large mass flow rate
- Iterative optimization is needed

# Major results

- To ensure a pinpoint landing, the initial state of the powered descent (PD) phase must match the range of engine thrust regulation and the estimate of $t_{go}$.
- The feasible physical region consists of two sets: reachable set and controllable set (Benito and Mease, 2010).



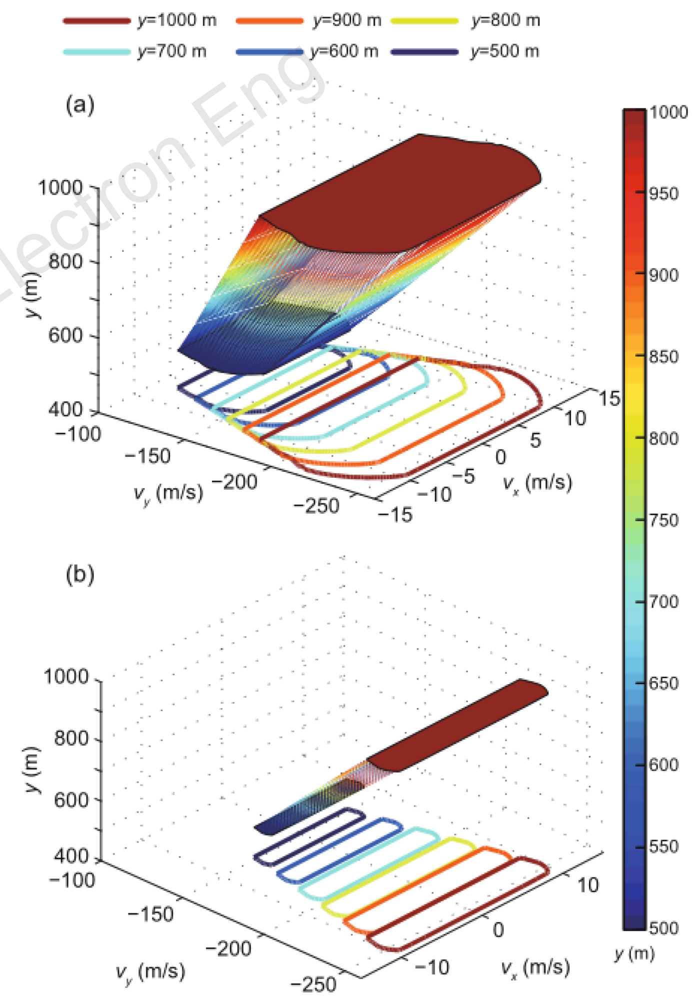


**Fig. 2** Access conditions for the powered descent phase: (a) $\tau = 65\%$; (b) $\tau = 90\%$

# Major results

- Any deviation in the model may shrink the feasible physical region in the landing process due to the limitations of the landing time and thrust regulation range, although the effect can be relieved by receding horizon control (RHC).
- Online prediction and model correction are necessary for improving the adaptability of AGM.
- The primal dual interior point method (PDIPM) automatically generates an initial guess, which deprives it of an effective means of improving the speed of the numerical algorithm with a warm start.
- The alternating direction method of multipliers (ADMM) is a framework for solving large-scale problems. It is easy to implement in parallel and distributed computing, and can be warm-started.

# Major results

- National space agencies and companies have designed the guidance, navigation, and control (GNC) demonstrators for various vertical landing scenarios.

| Demonstrator | Agency | Solver |
|---|---|---|
| Falcon | SpaceX | CVXGEN |
| New Shepard | Blue Origin | – |
| ADAPT | JPL | G-FOLD |
| EAGLE | DLR | ECOS |
| Peacock | CALT | ECOS |
| RLV-T3/T5 | LinkSpace | – |

(a) (b)

Fig. 3 Flight demonstrator: (a) EAGLE; (b) Peacock

# Conclusions

- A general problem description was formed, and three classes of methods, including analytical algorithms, numerical optimization algorithms, and learning-based methods, were discussed in detail.
- The efficiency and convergence of a method are deeply affected by engine configurations and the vehicle’s characteristics.
- Future research may continue focusing on a smart initial guess or the appropriate convexification strategy for non-convex problems.

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