Autonomous Spacecraft Landing Through Human Pre-attentive Vision and Optimal Control Theory

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Introduction

Efficiency in terms of mass and energy consumption, stability and adaptability with respect to unknown environments, intelligent behaviours in critical decision making processes, are all desirable features for autonomous spacecrafts. Interesting solutions to these issues can be found in nature: biological systems, indeed, possess autonomy by excellence. In this work, we present a bio-inspired approach to spacecraft landing that uses a model of human visual attention to guide the descent towards safe and interesting sites. The selected site for pin-point landing is, then, fed to an internal process which, based on optimal control theory, returns the thrust value necessary to execute the manoeuvres towards the target of interest. The novelty of our work stands from the use of a visual attention model, which provides the spacecraft with human perception abilities, in combination with a controller, which enables the robot (the spacecraft in our case) to select a proper action on the basis of simple representation of the self and of the world.

Unmanned Spacecraft Landing

Safe landing on celestial bodies is a fundamental step for space exploration. The current practice for landing missions design is based on off-line selection of landing sites: scientists examine and select aerial images obtained, a priori, via satellites. Once the landing site is selected, the spacecraft performs a 'blind' landing operation with little provision of corrective manoeuvres prior to touchdown [1]. Because of the relative inaccuracy of the landing path followed by the spacecraft, and of the relative uncertainty on the safety of the selected landing area, dangerous circumstances can occur and lead to mission failure. On-line remote control by human operators is an improbable and risky solution because of limited and unstable communication bandwidth and significant delays. For this reason, onboard reliable hazard and avoidance capabilities are a necessary requirement for next generation of autonomous unmanned spacecrafts.

In addition to the above issues, other two main factors influence landing mission design: reachability and scientific return. Reachability is an engineering problem which indicates fuel sufficiency associated to retargeting operations. Even when safe sites are identified, landing manoeuvres cannot be guaranteed if onboard fuel availability is neglected. Mission costs can also be reduced if landing sites are close to interesting locations, thus facilitating samples retrieval and increasing scientific return. Again, a pre-selection of multiple potential interesting sites is performed off-line by scientists. This procedure can be limiting during exploration of unknown environments, where undiscovered sites can contain novel unpredictable scientific findings. A example that well illustrates this limitation appears in *Planet 51*, the 2009 animated science fiction film written by Joe Stillman, where an intelligent rover, upon landing on a new planet, is able to collect only samples of stones and this imprinted selectivity leads it to consider the alien creatures living on the planet as uninteresting. If the rover had possessed the ability to visually discern intrinsic salient objects, instead of specific target only, it would not have missed the aliens.

While considerable work has been done for automating safe sites selection, using landmarks detection algorithms based on the onboard sensors capabilities [2]-[3]-[4]-[5] (i.e. craters detection, analysing cameras images, terrain features characterization, such as slope and roughness, processing RADAR and LIDAR signals), methods for interesting sites detection always refer to a priori maps, ranked by scientists according to specific scientific criteria. Because this last approach can affect the flexibility and constrain the autonomy of the lander, we propose to introduce in the control loop of the landing process a model which mimics human ability of selecting saliency in the visual field, thus providing the spacecraft with fast pre-attentive processes.

Continuous retargeting, during the descent, requires autonomous onboard re-planning of the guidance trajectory. We addressed this issue using an optimal feedback control based on a simplified spacecraft model and a coarse numerical grid. The chosen approach agrees with recent scientific findings on optimality principles found in the sensorimotor control of biological systems [6]-[7].

Model of Human Pre-attentive Vision for Autonomous Saliency Detection

Selective visual attention allows humans and animals to quickly shift the gaze towards specific attractive targets in the visual environment. This ability has evolutionary explanation: it enables organisms to rapidly detect their pray, escape from predators and recognize mates. In humans, attentive processes assume also an important role in higher cognitive mechanisms such as learning and memory.

According to studies on primate visual cortex [8], two different dynamical forms of attention can be identified: a pre-attentive form and a more complex form of attention. In the first form, also referred as 'bottom-up', simple features (such as, intensity, colour opponency and orientation) are processed rapidly and in parallel over the entire visual field and intrinsic saliency of objects is automatically detected. The second form, referred as 'top-down', is tuned by voluntary control, it is slower, conjugate features are processed serially, and the saliency of objects is dependent of specific task (or interest).

In this work, we focused on the 'bottom-up' attentional mechanism. Fast computation is, indeed, a requirement for real-time processing and onboard analysis; parallel neuro-biological architectures are suitable for implementation on VLSI (very-large-scale-integration) systems and FPGAs (Field-programmable Gate Array); detection of intrinsic saliency (mostly context-dependent and encoded in terms of center-surround mechanisms) provides major flexibility with respect to methods based on a priori knowledge.

The computational model, we used, is based on neuro-physiological findings and has been proposed first by Koch and Ullman (1985) [8], later extended by Itti et al. (1998) [9]. It can be described by the following steps: 1) early visual features are computed in a set of pre-attentive feature maps receiving input image; 2) the activity from all feature maps is combined at each location, giving rise to a topographic saliency map which codes for how different and how salient a particular stimulus is relative to its neighbourhood; 3) a winner-take-all network detects the most salient location and directs attention towards it; 4) an 'inhibition of return' (IOR) mechanism inhibits tagging of recently attended location and allows to shift to the next most salient location, endowing the search process with internal dynamics. This model has been proven to qualitatively reproduce human performances on a number of classical search experiments [10].

Optimal control for trajectory re-planning

In line with the ideas presented in [6]-[7] we developed a control feedback based on optimal control theory. The spacecraft uses a simplified model of itself (3 DOF) and a coarse time grid (3 points) to plan its thrust profile at each time instant (see Fig. 1 for a visual depiction of such a simplified internal representation of the world). Still, the resulting descent (see Fig. 2) turns out in a successful landing using only 1% more propellant mass but able to correct for imperfections in the dynamics and thrust actuation.

We demonstrated that same results are obtained by changing the final condition of the pin-point landing (which means imposing a different final landing point) and/or imposing a gravity-turn descent (which means constrains to zero the horizontal velocity at the landing point) or when any specific final position is required (free landing).

Landing Simulation

The proposed control architecture for the landing mission is schematically represented in Fig. 3. It is designed for the final path of the landing trajectory, starting from the high-gate position (at about 2.3 Km) and ending to the touchdown point.

PANGU 3.10 [11], planet surface simulator, has been used to generate Digital Elevation Maps (DEMs) which reproduce images acquired by the spacecraft's onboard camera.

At each position, the acquired image is processed by two modules: the *Neuromorphic Visual Attention* module, which includes the bio-inspired bottom-up model, computes a Saliency Map; the *Surface Variance Estimator* module produces a Safety Map or Hazard Map, where low variance areas are defined as safe landing sites. In Fig. 4 a snapshot of the maps provided by these two modules are shown: 5 salient points (blue crosses) and the safe location (red cross) closest to these interesting sites are projected onto the image of the planetary surface, about 200 meters below the spacecraft (Fig. 4a).

A parallel process passes through the *Optimal Control* module which computes a Cost Map, indicating the fuel consumption associated to the optimal trajectory. Given initial conditions and dynamics constraints, the implemented optimal control allows to estimate at each point and in real-time the thrust policy which maximizes the spacecraft mass.

The three maps enter a *decision-making process* module which estimates the candidate landing point according to safety, scientific return (represented by the Saliency Map) and fuel costs criteria. In the feedback control loop, the final landing position is input for *Optimal Control* module which updates the spacecraft trajectory.

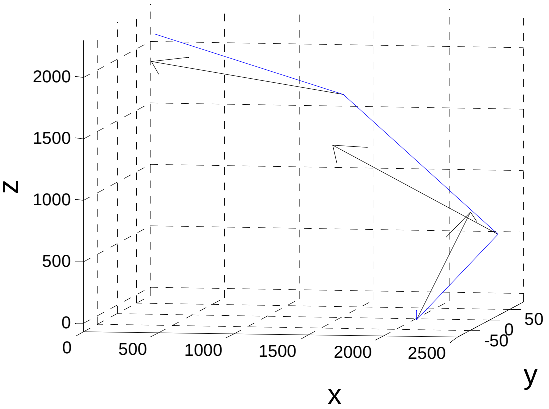

Fig. 1 Optimal Simplified Plan at the beginning of the simulation: since the 1st second of the simulation, the spacecraft is able to build an internal model of the reality by efficiently designing the entire trajectory (blue line) and estimating the thrust vectors (black arrows).

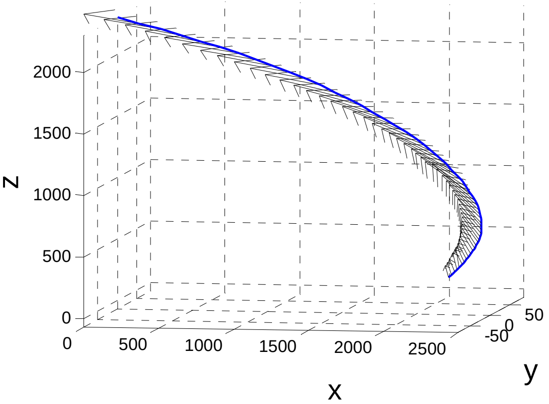

Fig. 2 Actual descent profile: external representation of the entire trajectory after 54 seconds, close to the touchdown instant.

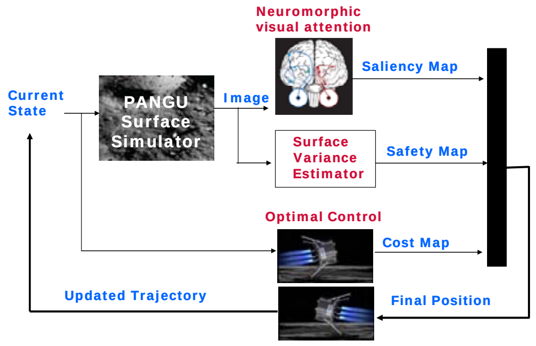

Fig. 3 Schematic of the control architecture

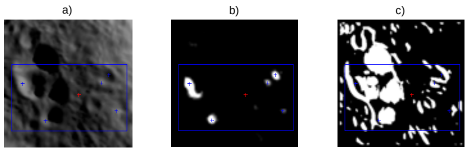

Fig. 4 Image Processing: a) image of the planetary surface below the spacecraft; b) Saliency Map; c) Safety or Hazard Map. The blue square indicates the region containing the first 5 more salient sites, blue crosses; the red cross points at the safe site closest to the salient points.

Conclusions

In this stage of the work, we tested the three modules (*Neuromorphic Visual Attention*, *Surface Variance Estimator* and *Optimal Control*) separately in Simulink environment. We showed how the integration of a pre-attentive process allows the spacecraft to exhibit human-like behaviours in the selection of salient landing sites. We also demonstrated that the proposed trajectory re-planning module, based on optimal control and on a simple internal model of the spacecraft self and of the world, provides for a robust and efficient autonomous landing architecture.

In this extended abstract we provided a brief overview of our system's components. In the final version of the paper we will present an in-depth discussion on their overall integration, along with a study of the real-time computing capabilities of such architecture.

A more extensive study of the trade-offs between simplicity in the estimated model of the world, and achievable optimality of the landing trajectory will be required, together with a platform for testing the system's performance with respect to a ground truth built on human judgements about saliency and safety issues.

Finally, we note that, though the described framework has been proposed for autonomous landing, it could also be readapted for application to navigation and exploration in unknown environments.

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