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Experimental investigation of stochastic parafoil guidance using a graphics processing unit

Nathan Slegers [a], Andrew Brown [b], Jonathan Rogers [b,*]

[a] Department of Mechanical Engineering, George Fox University, Newberg, OR 97132, United States
[b] Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA 30332, United States

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ABSTRACT

Control of autonomous systems subject to stochastic uncertainty is a challenging task. In guided airdrop applications, random wind disturbances play a crucial role in determining landing accuracy and terrain avoidance. This paper describes a stochastic parafoil guidance system which couples uncertainty propagation with optimal control to protect against wind and parameter uncertainty in the presence of impact area obstacles. The algorithm uses real-time Monte Carlo simulation performed on a graphics processing unit (GPU) to evaluate robustness of candidate trajectories in terms of delivery accuracy, obstacle avoidance, and other considerations. Building upon prior theoretical developments, this paper explores performance of the stochastic guidance law compared to standard deterministic guidance schemes, particularly with respect to obstacle avoidance. Flight test results are presented comparing the proposed stochastic guidance algorithm with a standard deterministic one. Through a comprehensive set of simulation results, key implementation aspects of the stochastic algorithm are explored including tradeoffs between the number of candidate trajectories considered, algorithm runtime, and overall guidance performance. Overall, simulation and flight test results demonstrate that the stochastic guidance scheme provides a more robust approach to obstacle avoidance while largely maintaining delivery accuracy.

1. Introduction

Current control algorithms for robotic systems are largely serial in nature. In the classical control paradigm, a sequence of serial steps is used to arrive at desired control inputs from feedback measurements. Over the past five decades, significant effort has focused on development of computationally efficient control algorithms to enable real-time execution on embedded microprocessors for robotic systems. Although computational performance of embedded devices continues to rapidly increase, the emphasis on algorithm computational efficiency remains a key characteristic of modern control design (for example, see (Hellstrom, Aslund & Nielsen 2010; Kothare & Wan, 2007; Duchaine, Bouchard & Gosselin 2007)). For deterministic systems at least, a variety of linear and nonlinear control algorithms now exist that offer suitable tradeoffs between computational complexity and performance (Blondel & Tsitsiklis, 2000).

Stochastic systems, or systems subject to large dynamic uncertainty, provide a unique challenge in terms of computational complexity because some element of uncertainty propagation must be inherent in the control formulation to ensure either robustness or optimality. In general, continuous systems subject to stochastic uncertainty do not admit closed-form or exact optimal control solutions and the certainty-equivalence principal does not hold (Blondel & Tsitsiklis, 2000). The exception is linear systems subject to Gaussian disturbances, in which the finite horizon optimal control problem may be solved exactly using dynamic programming recursion (linear quadratic Gaussian, or LQG, control). In the more general case of continuous nonlinear systems or non-Gaussian systems, new control formulations are needed that avoid the "curse of dimensionality" issues associated with dynamic programming techniques (Bars et al., 2006). In such cases, new advancements in high-throughput embedded computing may provide an avenue to practical implementation of optimal control for stochastic systems.

The thesis of this paper is that flexible optimal control algorithms incorporating nonlinear, non-Gaussian uncertainty propagation may be practically realizable for robotic systems through proper division of computational effort across a heterogeneous set of onboard embedded computing devices. By coupling standard microprocessors with emerging massively-parallel computing devices, uncertainty propagation and optimization may be performed in real-time without requiring restrictive assumptions of linear dynamics or Gaussian uncertainty. In this new class of optimal controllers, uncertainty propagation may be performed through real-time Monte Carlo simulation, and an optimal control action is determined by minimizing a cost function conditioned on the resulting probability density. Recent work by Ilg, Rogers, and Costello (2011) demonstrated the feasibility of executing real-time

* Corresponding author. Tel.: +1 404 385 1600.
E-mail address: jonathan.rogers@me.gatech.edu (J. Rogers).

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Nomenclature

$\mathbf{a}_{c/T}$	Acceleration of the parafoil mass center with respect to the inertial frame
C_i	Dimensionless parafoil aerodynamic coefficients
D	Distance of the turn initial point with respect to the target
e_i	Estimated mean miss distance for trajectory candidate i
$\mathbf{I}$	Inertia matrix of the parafoil-payload vehicle about the mass center
$\mathbf{F}_{AP}, \mathbf{F}_{AS}$	Aerodynamic forces on the parafoil and payload
$\mathbf{F}_{AM}$	Force on the parafoil-payload due to apparent mass effects
$\boldsymbol{F}_{WP}, \mathbf{F}_{WS}$	Weight forces on the parafoil and payload
$\mathbf{i}_T$, $\mathbf{j}_T$, $\mathbf{k}_T$	North-East-Down reference frame unit vectors
J_i	Cost associated with trajectory candidate i
k_g	Cost function weight for obstacle avoidance
L	Distance to target along target line
$\mathbf{M}_{AP}, \mathbf{M}_{AS}, \mathbf{M}_{AM}$	Moments from aerodynamics of the parafoil, payload, and apparent mass moments, all about the mass center
M	Number of possible yaw rate values used in discretization
N	Number of possible ψ_F values used in discretization
p_i	Estimated probability of obstacle impact for trajectory candidate i
R	Final turn radius
R_s	Number of candidate trajectories selection for Monte Carlo evaluation
$\mathbf{s}$	Parafoil 6DOF state vector
TIP	Turn initiation point
t_0	Time final turn begins
t_1	Time final approach begins
t_2	Time of predicted impact
T_{app}	Final approach time
V_h, V_z	Parafoil horizontal airspeed and vertical speed
W_x, W_y	Target frame wind speed components
x, y, z	Parafoil inertial positions in the North-East-Down frame
$\dot{x}, \dot{y}$	Parafoil inertial velocity components in the North-East-Down frame
ψ_F	Final approach angle
ψ	Parafoil Euler yaw angle
ψ_{max}	Maximum parafoil yaw rate
$\boldsymbol{\omega}_{B/T}$	Angular velocity of the parafoil-payload vehicle with respect to inertial frame

Monte Carlo simulations of air vehicle trajectories on graphics processing units (GPU's) given their data-parallel execution model.

The work described here explores this heterogeneous computing approach to stochastic control in the context of autonomous parafoil guidance and control. Parafoils are a type of controllable parachute used to deliver cargo and supplies to a specific target via release from an aircraft. In general, parafoil landing accuracy is adversely affected by unknown wind disturbances, which provide perturbations to the system on the same order as the vehicle airspeed. Largely as a result of wind uncertainty, current parafoil landing accuracy is limited to approximately 100 m, which is unsuitable for landing in environments with complex terrain or obstacles near the target (Benney, Meloni, Cronk & Tiaden, 2009; Tavan, 2006). Numerous authors have explored a variety of optimal parafoil guidance strategies including model predictive control (Slegers & Costello, 2005), direct glide slope control (Slegers, Beyer & Costello, 2008), and parametric path optimization (Slegers & Yakimenko, 2011; Ward, 2012; Fowler & Rogers, 2014). Gimadieva (Gimadieva, 2001) and Rademacher, Lu, Strahan, and Cerimele (2009) have proposed alternative optimal control strategies, the latter using modified Dubins paths. A key limitation of these solutions is that they are based on deterministic knowledge of the wind and thus may not be robust in cases of unknown winds or wind shifts during terminal flight. A deterministic solution may be appropriate based on the known mean wind; however, it could be extremely sensitive to variations in the wind, with a small change resulting in potential mission failure. For example, using a deterministic solution the optimal impact may occur close to an obstacle but still be considered acceptable. However, in the presence of uncertain winds, many potential trajectories may actually impact the obstacle. In contrast, a probabilistic solution would determine potential trajectory sensitivity to wind variation and as a result select a solution which reduces the probability of hitting the obstacle by shaping the terminal approach appropriately, even at the expense of slight reductions in landing accuracy.

Recently, the authors proposed a new method for stochastic parafoil terminal guidance in which Monte Carlo simulation is performed in real-time on a GPU co-processor (Rogers & Slegers, 2013; Slegers & Rogers, 2013). The GPU-derived Monte Carlo predictions are used to minimize a cost function that penalizes both impact point accuracy and other parameters such as drop zone constraint violations. Preliminary simulation results in Rogers and Slegers (2013) and Slegers and Rogers (2013) showed the ability of this guidance formulation to reshape impact dispersion patterns around arbitrary ground obstacles and terrain. This paper builds upon the theoretical foundations outlined in Rogers and Slegers (2013) and Slegers and Rogers (2013) to address various tradeoffs in guidance system performance and explore practical aspects of implementation. Specifically, the contributions of this paper include a discussion of the practical aspects of algorithm implementation on a flight vehicle, flight test results demonstrating performance of the stochastic guidance law in comparison to a standard deterministic guidance scheme, and an