Improving In-Flight Learning in a Flapping Wing Micro Air Vehicle

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ABSTRACT

Much effort has gone into improving the performance of evolutionary algorithms that augment traditional control in a Flapping Wing Micro Air Vehicle. An EA applied to such a vehicle in flight is expected to evolve solutions quickly to prevent disruptions in following the desired flight trajectory. Time to evolve solutions therefore is a major criterion by which performance of an algorithm is evaluated. This paper presents results of applying an assortment of different evolutionary algorithms to the problem. This paper also presents some discussion on which choices for representation and algorithm parameters would be optimal for the flight control problem and the rationale behind it. The authors also present a guided sampling approach of the search space to make use of the redundancy of workable solutions found in the search space. This approach has been demonstrated to improve learning times when applied to the problem.

KEYWORDS

Adaptive Hardware, Evolutionary Algorithms, Flapping-Wing Micro-Air Vehicle, Learning Times

INTRODUCTION

The construction and control of insect-scale Flapping-Wing Micro Air Vehicles (FW-MAVs) has been an area of considerable interest (Doman, 2009), (Doman, 2010), (Sane, 2001), (Wood, 2008). Vehicles of this style normally operate at a wing beat frequency of approximately 120 beats per second. This fairly fast flapping rate, among other considerations, suggests that basing vehicle position (location in space) and pose (rotations around vehicle axes) control upon wing beat cycle averaged forces is practical. In such a strategy, a vehicle feedback controller would, once per wing beat, decide what forces need to be applied to the vehicle to better achieve a desired position and/or pose. Using a pre-derived model that describes the relationship between wing motion through a single wing beat to generated force, each wing would be commanded to adopt a wing beat motion trajectory that, averaged over the entire wing beat, delivers the controller requested force. Naturally, any such strategy depends critically on two conditions:

1. The existence of a sufficiently accurate and precise model of cycle-averaged wing motion to force models; and

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2. Wings that are sufficiently undamaged that they comply with the model presumed to exist via item (1).

Even if one presumes condition (1), it should be noted that ongoing and accumulating wing damage will eventually cause violations of condition (2). It is not unreasonable to expect such damage. For real insects, normal flight results in permanent physical wing damage that is not healed. In fact, the age of many flying insects can be reliably estimated via accumulated wing damage (Cartar, 2011).

There are naturally multiple strategies one might employ to maintain condition (2) in the face of ongoing and accumulating wing damage. In previous work (Gallagher, 2012), (Gallagher, 2013), we adopted a strategy based on the idea of learning wing motion patterns that allowed damaged wings to comply with the motion-to-force models derived for undamaged wings. In short, the controllers for undamaged wings presumed cosine wing motion that was modulated by speed (frequency) and a single shape parameter that warped the cosine envelope in a manner defined later in this paper. Our previous work (Gallagher, 2013) employed an EA embedded in the oscillator to learn new periodic wing motion envelopes that would be modulated via the same frequency and shape parameter based warping functions. Over time, the wings would learn new motions that restored appropriate flight performance leaving the main controllers intact. EA learning in this context faces at least three particularly vexing challenges that stem from the requirement to modify wing motion envelopes without taking the vehicle out of service:

1. Learning must be accomplished while the vehicle is in normal service. There is no resetting of the vehicle’s state between evaluations of candidate wing motion definitions. This opens the door to serialized deceptive evaluations. In short, this means that evaluating a particularly bad candidate could place the vehicle in such a bad position that even a very good candidate cannot fully recover. This means that an otherwise good candidate would receive a bad fitness score essentially because of the poor performance of the candidate previously evaluated;
2. The EA system must find a workable, error correcting solution as quickly as possible. Taking several hours of flight time to correct a problem is not likely acceptable;
3. No candidate must be so bad that it catastrophically crashes the vehicle.

This paper will focus on improvements to items (1) and (2). Based on previous empirical work (Gallagher, 2012), we will presume that (2) is not a problem, although fuller consideration of that topic is definitely a relevant issue for additional study.

The paper begins with a description of the FW-MAV model which is used to simulate the above described control challenges that would be encountered in a physical vehicle and the modified adaptive controller employed for in-flight learning experimentation, followed by, a brief description of all the algorithms studied. Further, the paper provides some discussion as to which choices of algorithm parameters and representation impact learning times. This is followed by a section that explains the approach of guided sampled search for the solution in different regions of the search space that helps with reducing learning times. Finally, based on the insights gained from current work, the paper will conclude with a discussion of additional future work that can improve in-flight learning performance for practical real-world flight scenarios.
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