Performance Analysis of Multiobjective Bio-inspired UAV Path Planners

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ABSTRACT

This work aims to provide developers of bio-inspired UAV planners with a methodology to perform a systematic analysis of the results of their planners and support their algorithm parameter tuning based on this analysis. With that purpose, we propose to use some generic metrics capable of dealing with different dominance definitions and others that consider the final preferences of the experts. We apply them to a particular problem and show how to use them to identify the best planners within a big set.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem solving, control methods and search—*heuristic methods, plan execution, formation and generation*

General Terms

Algorithms

Keywords

Bio-inspired Algorithms, Multiobjective Optimization, Performance Measures, Parameter Tuning, UAVs

1. PROBLEM OVERVIEW

Unmanned Aerial Vehicles (UAVs) participate in many types of civil and military tasks, following a path obtained by an optimization algorithm that takes into account the UAV, mission and environment constraints and some optimality criteria (such as minimal path length and mission risk). The UAV optimal generation problem has already been tackled with Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE), providing good results as reported in [?, ?, ?]. However, a comparison of the performance among these techniques is not trivial, because the planners differ in their constraints/optimization criteria and in the path codification. Moreover, the experts usually introduce subjective decisions in their multi-objective problems (such as aggregated weighted sums, priorities, etc) preventing the comparison by means of any Pareto compliant indicators. This work aims to provide the UAV planning community with a methodology to analyze the performance of their multiobjective GA, PSO and DE planners and support their algorithm tuning. The proposed methodology uses some metrics that work with any pareto dominance definition while others provide meaningful information related with the experts preferences.

To illustrate the use of the metrics we use the complex military UAV planning problem presented in [?], which is formulated as an optimization problem where the UAV routes are compactly codified by a list of 3-D points that defines a spline curve, whose feasibility and optimality is evaluated according to 10 objective functions. These functions are related to the UAV physical constraints; the overflown terrain; and the disposition and characteristics of prohibited flying zones and probabilistically characterized air defense units. We rank/sort the trajectories within the heuristics using non-standard Pareto dominance definition based on priorities and goals proposed in [?], placing the 6 constraints in the higher priority level and the 4 optimization indexes in the next two levels. For a more detailed description, see [?].

We apply the metrics to 36 stochastic optimization planners that modify the values of the 3-D points of the list that define the splines, accordingly with the selected 10 objective values, the dominance evaluation method in [?], and the characteristics of the bio-inspired heuristic they are rooted in. There are 4 GA planners, based on NSGA-II, that differ in: the crossover and mutation operators, and the use of immigrants. We also have 16 PSO planners, based on OMOPSO, that differ in: the method that selects the global best, their parameter values, the use of immigrants, and the mutation operator. Finally, there are 16 DE planners that differ in: the mutation base vector selection, the mutation parameter setting, the mutation parameter range, and the crossover type. All the 36 planners use the non standard dominance definition of [?].

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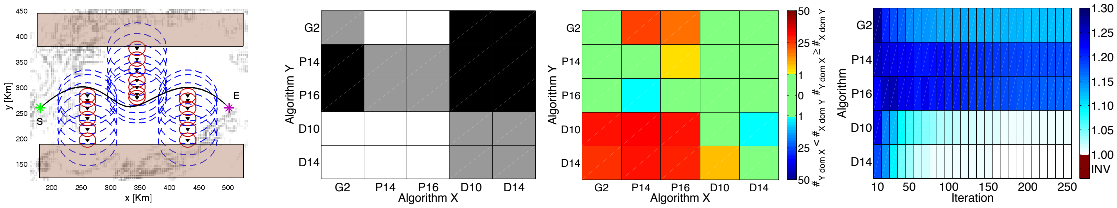

(a) Scenario (b) First metric (c) Second Metric (d) Third and Four Metric

Figure 1: Planners Comparison

2. PERFORMANCE METRICS

Due to the inherent stochasticity of the planners, we measure their performance applying several metrics to the results obtained in N_r different runs of each planner.

To consider the non-standard Pareto definition, we apply two metrics based on the weak dominance definition between two sets of solutions [?]. The first metric, the statistical front-dominance ranking procedure presented in [?], measures if the N_r results of algorithm Y are usually (and statistically) less dominated by the N_r results of algorithm X. The second one measures the number of times that the N_r results of algorithm Y dominate the results of algorithm X, when both are started with the same initial population. In short, the first lets us identify the planners that, when initialized with any population, obtain at least as good results as the others, while the second detects which planners improve further a given initial population. However, they only inform about the dominance of their outcomes.

To measure the goodness of the solutions and obtain meaningful metrics for the experts, we also consider their final preferences. The third metric calculates the number of best fronts that fulfill the constraints for the N_r results of each planner. The forth calculates the mean (for the N_r solutions of each planner) of the path length of the paths finally selected by the expert. Therefore, these metrics let the experts identify the planners whose solutions they might prefer.

3. RESULTS

To compare the performance of the 36 planners we calculate the values of the metrics for different subsets of planners over the results obtained with $N_r = 50$ optimizations for different UAV missions and graphically represent, as the examples in Fig. 1 show, the metric results to analyze them visually. The first metric graphics (Fig. 1b) show when the algorithm in the Y axis is better (their final solutions less dominated, *white*), equivalent (no statistically different, *gray*) or worst (their final solutions more dominated, *black*) than the algorithm in the X axis. The second metric graphics (Fig. 1c) show the number of times that the algorithm in the Y axis dominates the algorithm in the X axis, by means of a double-colored scale that also shows if the number of times that algorithm Y dominates algorithm X is bigger ($\#_{YdomX} \geq \#_{XdomY}$, *warm colors*) or smaller ($\#_{YdomX} < \#_{XdomY}$, *cold colors*) than the number of times that algorithm X dominates algorithm Y. Finally, the last graphic (Fig. 1d) shows the evolution, throughout the planner generations, of the third and forth metric, representing in *dark red* those generations where at least one of the N_r best fronts doesn't fulfill the constraints and in a blue scale, the mean path length of the generations that fulfill the constraints, employing *lighter colors* for its lower values (better) and *darker* for the higher values (worse).

The analysis of the graphics for 4 scenarios and all the different subsets of planners (not included for lack of space), shows that: 1) all GA variants perform similarly at the end, although the ones with the crossover and mutation presented in [?] are better in the initial generations, and 2) that the PSO and DE planners with low parameters and selection among the best are usually the best PSO and DE variants. The comparison among the best variants of each planner, as the one presented in Fig. 1, shows that the best DE variants (D10 and D14) obtain better solutions than PSO and GA, and that in this case, the GA variant (G2) is better than the PSO (P14 and P16) (although in other scenarios the PSO variants perform better than the GA).

4. CONCLUSIONS

To confront the performance of multiple planners, we propose the use of generic metrics capable of dealing with any dominance definitions, and problem specific metrics that consider the expert preferences. The results show how they let us identify 1) the best variants of the bio-inspired planners for each scenario and 2) the set of parameters whose values improve/degrade the performance of each planner type.

5. ACKNOWLEDGMENTS

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