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Robust Optimisation using Voronoi-Based Archive Sampling

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ABSTRACT

A key issue in tackling robust problems is the appropriate selection of solutions from the uncertainty set associated with a putative design, in order to estimate its robust quality and therefore guide the search process. We consider here problems where the variation of performance is due to some variability in the actual design realised (due to *e.g.* engineering tolerances), and the uncertainty set is therefore some disturbance neighbourhood around a design. We outline a framework, first reported in [Doherty et al., 2018], for online estimation solution quality in a robust optimisation setting by exploiting samples from the search history and using Monte Carlo sampling to approximate a Voronoi tessellation of the design space. Voronoi tessellations (and their Euclidean dual graphs, Delaunay triangulations) have a wide range of applications across the natural sciences [Aurenhammer, 1991]. The Voronoi tessellation of a set of discrete points in a continuous space divides the space into a set of *cells*, one for each point, so that for each point, its corresponding cell contains the volume of space that is closest to it. A useful feature of the Voronoi tessellation is that the point that is furthest from all of the points used to generate the tessellation will be a vertex of one of the cells. Therefore, a Voronoi tessellation provides us with a finite set of candidate points for the farthest point from all others. This is used to determine a new point in the disturbance neighbourhood of a given solution such that — along with the relevant archived points — they form a well-spread distribution. This approach is integrated within the widely used Covariance Matrix Adaptation–Evolution Strategy (CMA-ES) [Hansen & Ostermeier, 2001]. It is also used to weight the archive points to mitigate any selection bias in the neighbourhood history.

We consider three robustness quality measures: the expected fitness with a uniform disturbance (UD); the expected fitness with a Gaussian disturbance (GD); and the 95th percentile of fitness values, with a uniform disturbance (PC). We assess the performance of our framework on benchmark problems with different properties and design dimensionality [Paenke et al., 2006, Branke & Fei, 2016] and compare the results with existing frameworks that incorporate the search history in the estimation of solution robustness [Tsutsui & Ghosh, 1997, Branke, 1998, Tsutsui, 1999, Tsutsui & Ghosh, 2003, Kruisselbrink et al., 2010, Branke & Fei, 2016, Fei et al., 2018]. Our method performs competitively with these, and may be considered a new state-of-the-art approach for optimising such problem types.

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