ADAPTIVE GRID ARCHIVING COMBINED WITH THE COVARIANCE MATRIX ADAPTATION EVOLUTION STRATEGY

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BACKGROUND

The quality of Evolutionary Multiobjective Optimisation (EMO) solution sets can be measured by their pertinency, proximity, and diversity. The Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) is a state-of-the-art evolutionary algorithm first introduced in Hansen and Ostermeier (1996), designed to solve non-linear and non-convex optimisation problems in a continuous domain. The CMA-ES offers fast convergence, however it does not incorporate any techniques for the preservation of diversity amongst candidate solutions. In order to encourage preservation of diversity in the CMA-ES and produce a final candidate solution set with a satisfactory spread, an Adaptive Grid Archiving (AGA) system inspired by the Pareto Archived Evolution Strategy (PAES) introduced in Knowles and Corne (1999) has been combined with the CMA-ES, in a new algorithm named the Covariance Matrix Adaptation Pareto Archived Evolutionary Strategy (CMA-PAES), illustrated in figure 1.

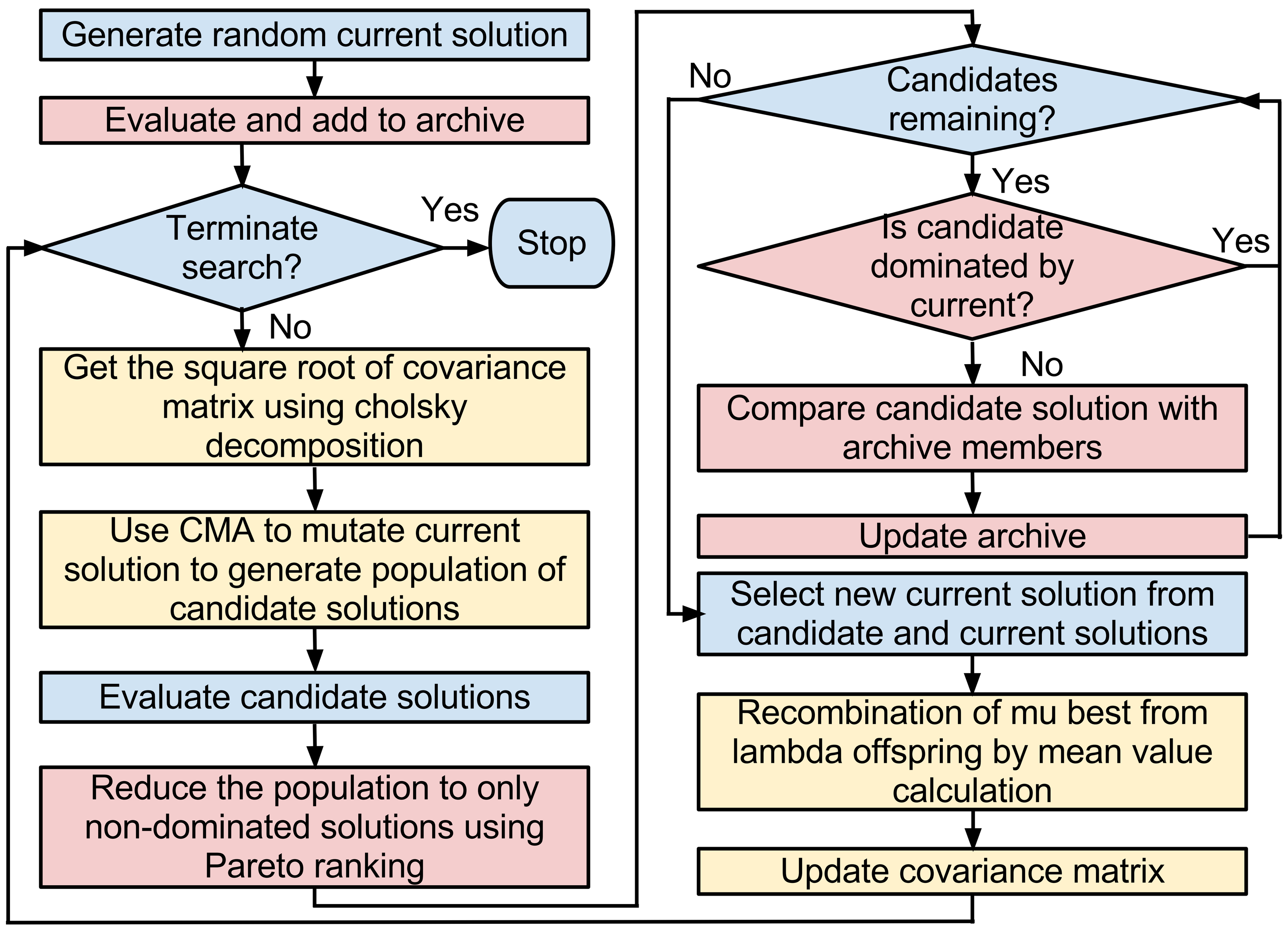

Figure 1: Flow chart illustrating the CMA-PAES algorithm. Blue indicates stages mutual within most EMO algorithms; yellow indicates stages specific to the CMA-ES algorithm; red indicates stages specific to the AGA used in PAES.

PURPOSE

The purpose of this research is to improve upon the CMA-ES algorithm, by incorporating the AGA from PAES to improve the diversity of solutions provided at the end of the EMO process.

METHODS

Both CMA-ES and CMA-PAES were tested using the ZDT suite of test functions defined in Zitzler et al. (2000). The test suite contains six test functions, ZDT1 through to ZDT6, with each function incorporating a feature that is known to cause the EMO process difficulty in convergence to the Pareto-optimal front. ZDT5 was not included in the experiment due to the requirement for binary represented decision variables. Each algorithm was tested using the parameters specified in table 1.

Due to the EMO process being stochastic by nature, each algorithm was executed 100 times against each test function, in an effort to minimise stochastic noise and increase the integrity of the comparison between the two algorithms. The performance of each algorithm execution was then measured using metrics to assess the quality of the approximation set, in terms of proximity to the true Pareto-optimal front and the diversity of solutions in the population.

Parameter	*Value*
Generations	15
Offspring population size	400
Parent population size	100
Archive size	100

Table 1: Algorithm configuration values for the CMA-ES and CMA-PAES.

A statistical comparison between the CMA-ES and the CMA-PAES was performed by computing the t-values of the performance results produced by each algorithm. Randomisation testing was then used to analyse the significance of these results, an advantage of this approach is that randomisation testing is a non-parametric test, and therefore does not require any assumptions to be made about the data (Manly,1991).

RESULTS

The following are the results of the randomisation testing conducted on the diversity metrics, these are shown graphically. The randomised distribution is presented as a histogram, and the observed result is marked as an asterisk on the x-axis. An observed result marked to the left of the histogram indicates that the CMA-PAES outperforms (provides a more diverse population) the CMA-ES, similarly an observed result to the right indicates the opposite is true. An observed result marked towards the middle of the histogram indicates that any difference in performance has occurred by chance.

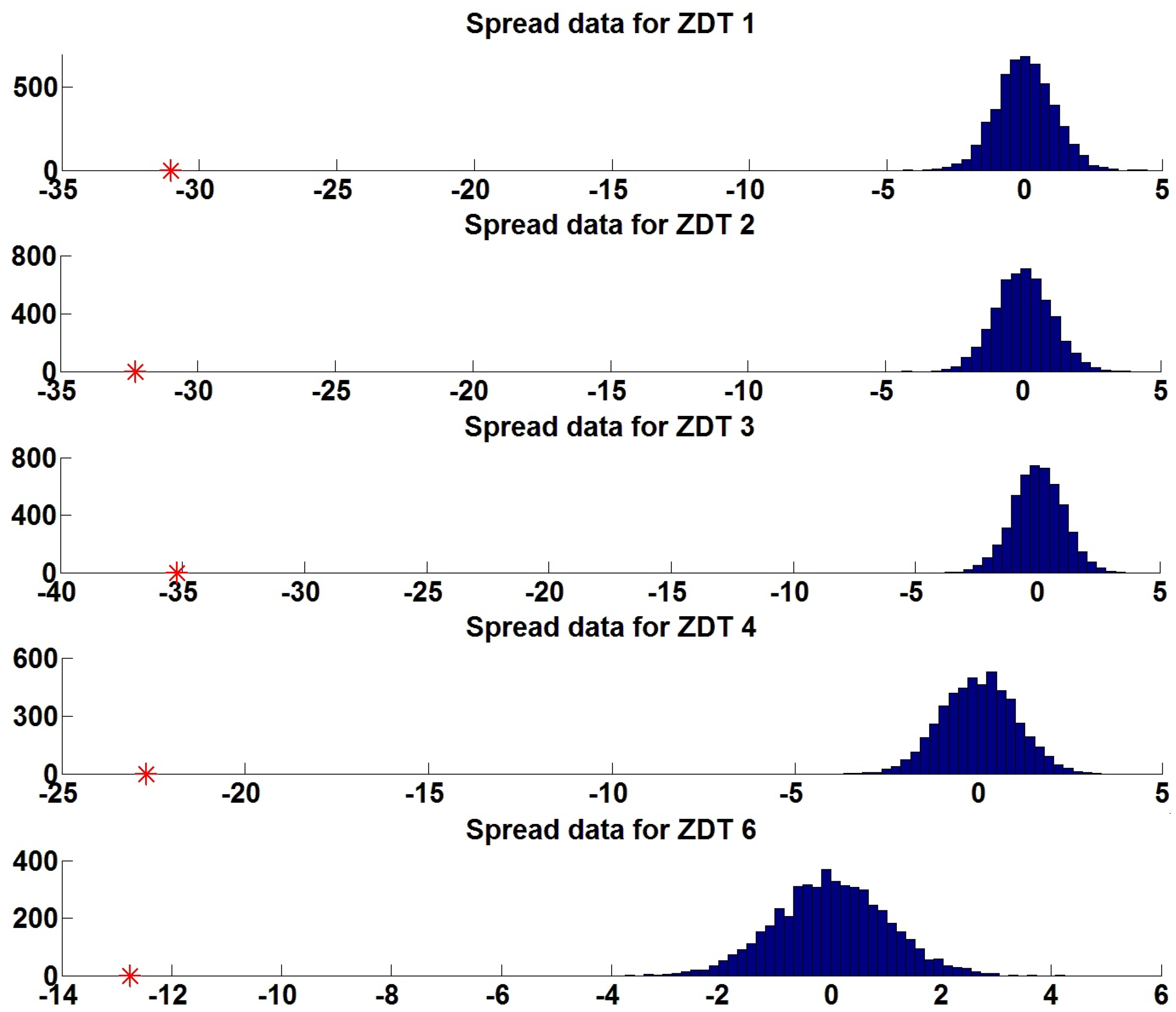

Figure 2: Randomisation data for the ZDT test functions. The x-axis describes the t-value, the y-axis describes the frequency.

CONCLUSION

The results suggest that AGA consistently improves the diversity of solutions in the CMA-PAES, and in that regard, the CMA-PAES outperforms the CMA-ES. As expected, there is no significant difference in performance when it comes to proximity of solutions in either algorithm.

FURTHER WORK

Further work to the CMA-PAES is recommended to improve the pertinency of its final solution set. This can be achieved by using preference articulation techniques, allowing focus and encouragement towards a desired region of interest during the optimisation process. A review and discussion of some popular methods of incorporating preference articulation into an EMO can be found in Coello (2000).

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