Exploratory Landscape Analysis Using Algorithm Based Sampling

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ABSTRACT

Exploratory landscape analysis techniques are widely used methods for the algorithm selection problem. The existing sampling methods for exploratory landscape analysis are usually designed to sample unbiased candidates for measuring the characteristics of the entire search space. In this paper, we discuss the limitation of the unbiased sampling and propose a novel sampling method, which is algorithm based and thus biased. Based on the sampling method, we propose several novel landscape features which are called algorithm based landscape features. The proposed features are compared with the conventional landscape features using supervised and unsupervised learning. The experimental results show that the algorithm based landscape features outperform the conventional landscape features.

KEYWORDS

Evolutionary algorithm; algorithm selection; algorithm based landscape feature; exploratory landscape analysis.

1 INTRODUCTION

Exploratory landscape analysis (ELA) techniques are the most widely used methods dealing with algorithm selection problem. They aim at extracting features for a problem prior to optimization. Sampling techniques can signficiantly affect properities of ELA features. A recent survey lists different sampling strategies for fitness landscape analysis [1]. They are random walk, adaptive walk, reverse adaptive walk, "uphill-downhill" walk, neutral walk and population-based "walks". The sampling method in this paper belongs to the population-based "walks" group. Instead of defining new features as we run an algorithm, we propose the methodology of constructing algorithm based features by concatenating an algorithm with an ELA feature. These algorithm based features will be compared with existing landscape features.

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2 LIMITATION OF THE EXISTING LANDSCAPE FEATURES AND AN IMPROVEMENT

In an algorithm selection method, finite candidates are sampled to estimate the fitness landscape. The conventional sampling methods try to measure the characteristics of the entire search space. The fact that the performance of an algorithm on a problem instance mainly depends on the characteristics of certain regions of the search space rather than the entire search space is overlooked. Almost all existing landscape features are computed using the candidates distributed in the entire search space. However, an efficient optimization algorithm will focus on parts of the search space after several generations, i.e., many candidates contribute little to predicting the performance of the algorithm. Thus we propose our novel algorithm based sampling method and algorithm based landscape features which carry more useful landscape information and perform better than the conventional landscape features. For a given problem instance and a given sample size λ, the processes that extract the algorithm based features are designed as follows: We run an optimization algorithm on the given problem with λ evaluations. Candidates generated in the first quarter of the evaluation budget will not be used to compute the algorithm based feature values. The rest of the candidates are used to extract landscape features. The extracted biased landscape features are the proposed algorithm based landscape features.

In this paper, we propose two types of novel algorithm based landscape features. They are Artificial bee colony (ABC) based landscape features and differential evolution (DE), more specifically, composite DE based landscape features. Suppose the sample size is λ, to reduce the randomness of the feature result, candidates generated in the first quarter of the evaluation budget will not be used to compute the algorithm based feature values, although λ candidates are evaluated. We implement the algorithm based version of 5 widely used landscape features for comparison. They are fitness-distance analysis (FDC), dispersion metric ($DISP_{1\%}$, 1% fittest candidates), evolvability (EVO), probability of convexity (PC) and entropy (ENT) [2].

3 EXPERIMENTAL RESULTS

To investigate the effectiveness of the proposed algorithm based landscape features, we apply them to the fitness landscape of the BBOB noiseless suite [3]. The search space is set to $[-5, 5]^D$. The suite consists of 24 noiseless continuous functions. Different instances of a function are generated from the original function by translating and rotating. In this section, 5 ABC based and 5 DE based landscape features are extracted and compared with the conventional landscape features. The prefixes ABC-, DE- and Conv- are added to the feature names denoting they are ABC based features, DE based features and conventional features respectively. The BBOB noiseless suite is manually classified into 5 classes [3].

Table 1: The purity values of the clustering results. The values are averaged over 30 independent experiments. Values are bold if significantly better.

Feature name	D=5	D=10	D=20
Conv-features (λ = 500)	0.870	0.864	0.843
ABC-features (λ = 500)	**0.907**	**0.894**	**0.866**
Conv-features (λ = 500)	0.870	0.864	0.843
DE-features (λ = 500)	**0.953**	**0.927**	**0.880**
Conv-features (λ = 1000)	0.898	0.886	**0.871**
ABC-features (λ = 1000)	0.910	0.903	0.857
Conv-features (λ = 1000)	0.898	0.886	0.871
DE-features (λ = 1000)	**0.960**	**0.934**	0.888
Conv-features (λ = 2000)	0.916	0.897	**0.878**
ABC-features (λ = 2000)	0.926	0.908	0.864
Conv-features (λ = 2000)	0.916	0.897	0.878
DE-features (λ = 2000)	**0.984**	**0.952**	0.895

Table 2: The Mean Absolute Error (MAE) of the features. The result values are averaged over 30 independent experiments. Values are Bold if significantly better.

Feature name	D=5	D=10	D=20
Conv-features (λ = 500)	0.694	0.798	0.851
ABC-features (λ = 500)	**0.637**	**0.728**	**0.798**
Conv-features (λ = 500)	0.694	0.798	0.851
DE-features (λ = 500)	**0.603**	**0.752**	0.840
Conv-features (λ = 1000)	0.692	0.756	0.791
ABC-features (λ = 1000)	**0.627**	**0.699**	0.789
Conv-features (λ = 1000)	0.692	0.756	**0.791**
DE-features (λ = 1000)	**0.542**	**0.717**	0.821
Conv-features (λ = 2000)	0.685	0.728	0.770
ABC-features (λ = 2000)	**0.600**	**0.698**	0.782
Conv-features (λ = 2000)	0.685	0.728	0.770
DE-features (λ = 2000)	**0.503**	**0.636**	0.780

3.1 Comparison of clustering quality

In this experiment, we investigate the performance of the proposed landscape features using unsupervised learning. We use the K-means clustering method ($K = 5$) to cluster these feature vectors. The purity values are computed to quantitatively evaluate the clustering quality by referring to an ideal clustering result. The range of the purity value is [0, 1]. A higher purity value indicates a better clustering quality. We select a function for each class. Thus we compose a subset consisting of 5 functions from the 5 classes. The selected functions are f_1, f_8, f_{11}, f_{17} and f_{23}. For each function instance, their conventional and algorithm based landscape features (FDC, DISP, EVO, PC and ENT) are extracted and concatenated, composing 5-D feature vectors respectively. The purity values of the clustering results for the algorithm based landscape features and the conventional landscape features extracted from 20 different instances for each function with dimensions $D = 5, 10, 20$ and sample sizes $\lambda = 500, 1000, 2000$ are computed. The experiment is independently repeated 30 times. The average purity values are shown in Table 1. We use Mann-Whitney U-test ($\alpha = 0.05$) to test the significance. Significant results are shown in bold. In total, there are 18 pairs of comparisons in Table 1, and 10 pairs show that the algorithm based landscape features are significantly better. The rest has no significant differences.

3.2 Expected running time prediction

In the next experiment, we aim at investigating the performance of the proposed features using supervised learning. We use a linear regression model to predict the logarithm of the expected running time ($\log_{10} ERT$) of the BIPOP-aCMA for reaching precision 10^{-7}. The entire BBOB suite consisting of 24 functions is used for training and testing. The experiment is designed as follows: We extract feature vectors from 15 different function instances for each benchmark function. Thus $360 = 15 \times 24$ 5-D feature vectors are extracted and used for training the linear regression model. After the training, for each function, 5 new instances are used for testing. We predict their $\log_{10} ERT$ and compute the mean absolute error (MAE) between the predicted $\log_{10} ERT$ and the reference $\log_{10} ERT$ to evaluate the performance of the linear regression model. A smaller MAE value indicates a better prediction. The experiment is independently repeated 30 times. The average MAE values are shown in Table 2. We use Mann-Whitney U-test ($\alpha = 0.05$) to test the significance. Significant results are shown in bold. In total, there are 18 pairs of comparisons in Table 2, and 13 pairs show that the algorithm based landscape features are significantly better. The rest has no significant differences.

4 CONCLUSION

In this paper, we propose an algorithm based sampling method and a set of novel features called algorithm based landscape features. These features are computed by concatenating an algorithm with an existing ELA feature. The algorithm based features and the conventional features are compared by clustering quality and expected running time prediction. The experimental results suggest that algorithm based sampling may make a feature more effective.

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