# Migration of Probabilistic Models for Island-Based Bivariate EDA Algorithm 

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#### Abstract

The paper presents a new concept of parallel bivariate EDA algorithm using the island-based model with the ring topology. The traditional migration of individuals is compared with a newly proposed technique for the migration of probabilistic models.


## Categories and Subject Descriptors

I.2.6 [Artificial Intelligence]: Learning.
G. 3 [Probability and statistics]: Multivariate statistics.

## General Terms

Algorithms.

## Keywords

Evolutionary algorithms, EDA algorithms, island-based models, migration, learning of probabilistic models.

## 1. INTRODUCTION

The well known representative of sequential bivariate EDAs is the Bivariate Marginal Distribution Algorithm (BMDA) proposed by Pelikan and Műehlenbein [1]. The aim of a new concept of BMDA parallelization is to discover the efficiency of the probabilistic parameter transfer in comparison to the traditional individual migration.

## 2. PROBABILISTIC MODEL

The population is structured in the form of island subpopulations using the unidirectional ring topology. We proposed a way for combining the probabilistic model of currently active resident island with the immigrant one from the neighbor. In particular, if $\boldsymbol{M}_{\boldsymbol{R}}$ is the model of a resident island and $\boldsymbol{M}_{\boldsymbol{I}}$ is the immigrant model, the new model $\boldsymbol{M}_{\boldsymbol{R}}^{\prime}$ is obtained by formula (as in [2]):

$$
M_{R}^{\prime}=\beta M_{R}+(1-\beta) M_{I}
$$

where $\boldsymbol{M}=(\boldsymbol{G}, \boldsymbol{\Theta})$, with $\boldsymbol{G}$ is a dependency graph and $\boldsymbol{\Theta}=\left(\theta_{1}, \theta_{2}, \ldots, \theta_{n}\right)$ is a set of model parameters for $n$-size problem. The new dependency graph $\boldsymbol{G}_{\boldsymbol{R}}^{\prime}$ is built according to a Chi-square metric:

[^0]$$
\chi_{i, j}^{2}=\beta \chi_{i_{R}, j_{R}}^{2}+(1-\beta) \chi_{i_{I}, j_{I}}^{2} ; i, j \in\{1, \ldots, n\}
$$

The adaptation coefficient $\beta$ is determined by the average fitness function of the resident and immigrant subpopulation:

$$
\beta= \begin{cases}\frac{F_{R}}{F_{I}+F_{R}} & \text { if } F_{I} \geq F_{R} \\ 0.9 & \text { otherwise }\end{cases}
$$

The new resident probabilistic model is then stated as $\boldsymbol{M}_{\boldsymbol{R}}^{\prime}=\left(\boldsymbol{G}_{\boldsymbol{R}}^{\prime}, \boldsymbol{\Theta}_{\boldsymbol{R}}^{\prime}\right)$ and a new subpopulation is generated by sampling the built model.

## 3. CONCLUSION

The newly proposed algorithm was tested on the well known benchmarks like OneMax, TwoMax, Quadratic and 3-Deceptive problem. We used three evaluation metrics: success rate, number of building blocks and the mean value of fitness function. Experimental results confirmed our expectation that migration of the probabilistic model with adaptation can yield significantly better results than the migration of individuals. In case of Quadratic and 3-Deceptive benchmarks the size of problems solvable by the proposed algorithm (with 100 percent success rate and fixed population size) increased two times.
The future work will be focused on the parallelization of the Bayesian Optimization Algorithm (BOA).

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