Solving dynamic multi-objective problems using a copula-based estimation of distribution algorithm

Conference Paper · October 2016

2 authors:

Abdelhakim Cheriet
Université Kasdi Merbah Ouargla

Cherif Foudil
Université de Biskra

Solving dynamic multi-objective problems using a copula-based estimation of distribution algorithm

A. Cheriet and F. Cherif

LESIA Labratory,Biskra University, Algeria
ahcheriet@gmail.com
foud_cherif@yahoo.fr

1 Introduction

The most real world problems are multi-objective, we have to add that many real world problems are also dynamic or continuously changing over a period. Changes may affect the object function, the problem instance, and/or constraints. In the literature of optimization in dynamic environments,researchers usually define optimization problems that change over time as dynamic problems or time-dependent problems [1].

A dynamic multi-objective problem can be represented as the following multi-objective optimization problem [2]. Let t be the time variable,$\mathbf{V}$ and $\mathbf{W}$ be n-dimensional and M-dimensional continuous or discrete vector spaces,$\mathbf{g}$ and $\mathbf{g}$ be two functions defining inequalities and constraints, and $\mathbf{f}$ be a function from $\mathbf{V} * t$ to $\mathbf{W}$. A dynamic multi-objective minimization problem with M objectives is defined as:

$$\begin{cases} \min\limits_{v \in V} f = \left\{ (f_1(v,t), \ldots, f_M(v,t) \right\} \\ s.t \quad g(v,t) \leq 0, h(v,t) = 0 \end{cases} \tag{1}$$

In this work, we present a new memory-based algorithm to solve a class of dynamic multi-objective problems. We use a copula-based estimation of distribution algorithm as a method of optimisation to get Pareto solutions in every generation of the algorithm. The obtained estimation model created using copulas will be utilized as a memory. We employ the memory created when a modification occurs during the execution of the optimisation process. The proposed EDA estimate in every generation the distribution of the best Pareto solutions obtained so far by creating a copula that describes the dependency between those solutions. We suppose that the created copulas can be used as a memory because they, not only save the last obtained best solutions but, save an explicit representation of the best solutions. The generated individuals from this explicit representation will be used as an initial population when a change occurs to the problem. We tested our proposal on the CEC2015 [3] benchmarks and we find that our algorithm gives good results.

An Estimation of Distribution Algorithm (EDA) is a class of the evolutionary algorithms that aims to estimate a distribution of a set of solutions usually the best ones, and use this estimation to generate new ones in every generation. The main difference between an EDA to another optimization algorithm is the manner of the estimation and the fashion of the algorithm implementation.

In Mathematics, a Copula is used to describe the dependencies between random variables. The proposed Copula-based EDA helps to create the estimator of the EDA. After finding the optimal solutions - like any classical optimization Algorithm - the generated Copula Model can be used when a change is detected in the problem. To validate our proposal, the proposed algorithm is performed to find the optimal solutions of a set of benchmark problems using the MOEA/D [4] as selection method.

2 The Proposed Copula-based Estimation of Distribution Algorithms

The Estimation of Distribution Algorithms uses many ways to estimate the distribution of the best solutions, we can find in [5] a good description of the used methods of estimation, however the use of Copula to estimate the distribution in EDA is a very strong idea to optimize complex problems [6–8]. We referred to copulas as "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions and as distribution functions whose one-dimensional margins are uniform." [9]. Many types of Copula have been applied in various research studies such as [10] and [11–14], in this paper, we will use an Archimedeon copula to find the best estimation.

Algorithm 1 Dynamic Copula-based EDA

$Q_0 \leftarrow$ Initialization(N_0)
$NDSet_0 \leftarrow$ Sorting(Q_0)
$P_0 \leftarrow$ SelectFromNDS(N)
$t \leftarrow 1$
while Not termination criteria **do**
  if Change Detected **then**
    $C_t \leftarrow$ EstimateMarginal(P_{t-1})
    $P_{tmp} \leftarrow$ GenerateSolutions(C_t)
  end if
  $NDSet_t \leftarrow$ ApplyMOEAD($P_{tmp} \cup NDSet_{t-1}$)
  $P_t \leftarrow$ SelectFromNDS(N)
  $NDSet_t \leftarrow P_t$
  $t \leftarrow t+1$
end while
Return $NDSet_t$,C

Like any evolutionary algorithm, our proposed method has two main steps; the *Selection* and the *Reproduction*, in the first step, we use the MOEA/D to select the best solution which will be used in the second step called the Reproduction, in this second step, the Copula is applied to estimate, then to regenerate new individuals. When a change occurs in the problem our proposal uses the obtained Copula model to generate individuals and use them as an initial population in the next generation. A pseudo-code of the Estimation of distribution algorithm using a Copula for a dynamic multi-objective problem illustrated in Algorithm 1.

3 Experimentation

To proof the efficiency of the proposed algorithm, a set of tests has been conducted using a set of benchmarks which are usually used in this kind of problems trying to test new solving algorithms in the area of dynamic multiobjective optimization. The work CEC2015 [3] provide a set of test benchmarks to compare the new algorithms with the classical algorithms. We used especially FDA4, FD5, HE2 and DMOP2 benchmarks in experimentations to proof the results given by our proposal.

4 Conclusion

In this work, we have proposed an Estimation of distribution Algorithm. The proposed algorithm used an estimation method which is the Copula and a very famous type which is the Archimedean one. Then we made an application of the new Copula-based EDA algorithm to solve Dynamic Multiobjective Optimization Problems. We used the obtained Pareto Solutions Estimated Model to generate new Pareto Solutions when the problem change. The Copula Model is viewed as a memory that conserves the characteristics of the PS, this vision is the motivation of using this algorithm in the Dynamic Multiobjective algorithm. A future work can be the use of the Copula Model as a memory in class of Real World Dynamic Multiobjective optimization problems.

References

1. Nguyen, T.T., Yang, S., Branke, J.: Evolutionary dynamic optimization: A survey of the state of the art. Swarm and Evolutionary Computation **6** (2012) 1–24
2. Farina, M., Deb, K., Amato, P.: Dynamic multiobjective optimization problems: test cases, approximations, and applications. Evolutionary Computation, IEEE Transactions on **8** (2004) 425–442
3. Helbig, M., Engelbrecht, A.: Benchmark functions for cec 2015 special session and competition on dynamic multi-objective optimization. Technical report, (Technical report)

4. Zhang, Q., Li, H.: Moea/d: A multiobjective evolutionary algorithm based on decomposition. Evolutionary Computation, IEEE Transactions on **11** (2007) 712–731
5. Hauschild, M., Pelikan, M.: An introduction and survey of estimation of distribution algorithms. Swarm and Evolutionary Computation **1** (2011) 111–128
6. Cheriet, A., Cherif, F., Taleb-Ahmed, A.: Fast solutions enhancing using a copula-based eda and svm for many-objective problems. IFAC-PapersOnLine **49** (2016) 781 – 786 8th {IFAC} Conference on Manufacturing Modelling, Management and Control {MIM} 2016Troyes, France, 2830 June 2016.
7. Wang, L.F., Zeng, J.C.: Estimation of distribution algorithm based on copula theory. In: Exploitation of linkage learning in evolutionary algorithms. Springer (2010) 139–162
8. Salinas-Gutiérrez, R., Hernández-Aguirre, A., Villa-Diharce, E.R.: Using copulas in estimation of distribution algorithms. In: MICAI 2009: Advances in Artificial Intelligence. Springer (2009) 658–668
9. Nelsen, R.B.: An introduction to copulas. Springer (2006)
10. Gao, Y., Peng, L., Li, F., Liu, M., Hu, X.: Eda-based multi-objective optimization using preference order ranking and multivariate gaussian copula. In Guo, C., Hou, Z.G., Zeng, Z., eds.: Advances in Neural Networks ISNN 2013. Volume 7952 of Lecture Notes in Computer Science. Springer Berlin Heidelberg (2013) 341–350
11. Wang, X., Gao, H., Zeng, J.: Estimation of distribution algorithms based on two copula selection methods. Int. J. Comput. Sci. Math. **3** (2012) 317–331
12. Chang, C., Wang, L.: A multi-population parallel estimation of distribution algorithms based on clayton and gumbel copulas. In: Artificial Intelligence and Computational Intelligence. Springer (2011) 634–643
13. Wang, L., Guo, X., Zeng, J., Hong, Y.: Using gumbel copula and empirical marginal distribution in estimation of distribution algorithm. In: Advanced Computational Intelligence (IWACI), 2010 Third International Workshop on, IEEE (2010) 583–587
14. Cheriet, A., Cherif, F.: A posteriori pareto front diversification using a copula-based estimation of distribution algorithm. (IJACSA) International Journal of Advanced Computer Science and Applications **6** (2015) 13