An Evaluation of Cellular Population Model for improving Quantum-inspired Evolutionary Algorithm

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ABSTRACT

This work empirically evaluates the impact of Von Neumann Cellular population model on Quantum inspired Evolutionary algorithms (QEA), specifically for solving Massively Multimodal Deceptive Problem (MMDP) and Knapsack problems.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods.*

General Terms

Algorithms.

Keywords

QEA, MMDP, Combinatorial Optimization.

1. INTRODUCTION

Quantum inspired Evolutionary algorithms (QEA) are nature inspired population based search heuristics, which provides better balance between exploration and exploitation [1]. QEAs have performed better than classical Evolutionary Algorithms (EA) on many complex problems [2]. Further, investigations have also been made in using structured population to improve the performance of the EAs [3]. The structure of a population is classified as Panmictic, Coarse-Grained and Fine-Grained [5], [6]. QEA described in [1], cQEA, has employed a population structured as Coarse-Grained Model. The performance of this algorithm has been improved by changing the global update strategy in [2] and has been named as Versatile QEA (vQEA). The modification to convert cQEA into vQEA can be viewed as equivalent to changing the population structure from Coarse-Grained model to panmictic. The improvement attained by vQEA over cQEA indicates the impact of population topology on performance of QEA. This also motivates investigation into employing Fine-Grained model also known as Cellular model in population structure. This paper empirically evaluates the improvement in cQEA by applying Cellular Population Model with Von-Neumann topology by solving Massively Multimodal Deceptive Problem (MMDP) and Knapsack problems.

The QEA proposed in [1] & [2] primarily hybridizes the Superposition and Measurement principles of Quantum Computing in Evolutionary Computing framework by implementing qubit as Q-bit, which is essentially a probabilistic bit, and store α & β values. The Q-bit string acts as genotype of the individual and the binary bit string formed by collapsing Q-bit forms the phenotype of the individual. Further, the Q-bit is modified by using quantum gates [1]. A quantum gate known as Rotation gate has been employed in [1]. It acts as the main variation operator that rotates Q-bit strings to obtain good candidate solutions for the next iteration. It requires an attractor [2] towards, which the Q-bit would be rotated. It further takes into account the relative current fitness level of the individual and the attractor and also their binary bit values for determining the magnitude and direction of rotation. The selection of attractor is determined by the population model employed in QEA.

The proposed QEA, QEA-C-VN, has all the operators and strategies similar to that used in cQEA [1] and vQEA [2] except for the population model and the neighborhood topology. The population model is cellular and does not have local groups. Every individual is located in a unique position on a 2 dimensional toroidal grid, which is the most common topology in cellular model [3]. The size of the grid is A X B, where A is number of rows and B is number of columns. The neighborhood on the grid is defined by Von-Neumann Topology, which has five individuals i.e. the current individual and its immediate north, east, west and south neighbors. Thus, it is also called as NEWS or linear5 (L5) neighborhood Topology. The neighborhood is kept static in the current work so it is computed only once during a single run.

cQEA, vQEA and the proposed QEA-C-VN has been implemented as follows [1], [2]:

a) t = 0; Define Group Size;
b) initialize Q(t);
c) make P(t) by observing the states of Q(t);
d) evaluate P(t);
e) store the best solutions among P(t) into B(t);
f) while (termination condition is not met) {
g) t = t + 1;
h) make P(t) by observing the states of Q(t-1);
i) evaluate P(t);
j) Determine attractors Atr(t) based on Population model;
k) update Q(t) according to P(t) and Atr(t) using Q-gates;
l) store the best solutions among B(t-1) and P(t) into B(t);
m) store the best solution b among B(t) ;
n) if(migration condition is met) migrate b or b^t_j to B(t) globally or locally, respectively }

In step b), the qubit register Q(t) containing Q-bit strings for all the individuals are initialized randomly. In step c), the binary solutions in P(0) are constructed by observing the states of Q(0). In step d), each binary solution is evaluated to give a measure of its fitness. In step e), the initial best solutions are then selected among the binary solutions P(0), and stored into B(0). In step e1) if QEA-C-VN is used then compute neighborhood list. In step f) and g), iteratively, the binary solutions in P(t) are formed by observing the states of Q(t-1) as in step c), and each binary solution is evaluated for the fitness value. In step j), the attractors are determined for each individual according to the population model. In step k), Q-bit individuals in Q(t) are updated by applying Q-gates by taking into account Atr(t), b and P(t), which is defined as a variation operator of QEA. The variation operator is rotation gate. In step l) and m), the best solutions among B(t-1) and P(t) are selected and stored into B(t), and if the best solution stored in B(t) is better fitted than the stored best solution b, the stored solution is replaced by the new one. In step n), a migration condition is checked and if satisfied, the best solution b is migrated to B(t) or the best among some of the solutions in B(t), b^t_j, is migrated to them.

2. TESTING, RESULTS AND ANALYSIS

The testing is performed on all the three population models by using Massively Multimodal Deceptive Problem (MMDP) with K = 40 [4] and Knapsack problems with capacity limited to 20 [1]. The testing is performed with equivalent parameter setting for all the three algorithms and is given in Table 1.

Table 1. Parameter setting for cQEA, vQEA and QEA-C-VN

Parameters	cQEA	vQEA	QEA-C-VN
Population Size	15	15	15
Number of Observations	1	1	1
Local Group Size	3	N.A.	N.A.
Local Migration Period	1	N.A.	N.A.
Global Migration Period	100	1	N.A.
Toroidal Grid Size	N.A.	N.A.	5 X 3
Topology / Size	N.A.	N.A.	Von-Neumann / 5
Stopping Criterion	10000	10000	10000

The results of testing of all the algorithms on MMDP with K = 40 for 100 runs and Knapsack problem with items 100, 500 and 1000 for 30 runs have been presented in Table 2.

Table 2. Statistical Results on mean (std. dev.) of fitness value

Problems	cQEA	vQEA	QEA-C-VN
MMDP	39.17 (0.484)	38.9 (0.559)	39.19 (0.574)
Knapsack (100)	73.49 (3.5)	70.99 (3.05)	82.49 (3.4)
Knapsack (500)	84.33 (4.69)	84.66 (5.71)	91.99 (5.96)
Knapsack (1000)	84.98 (6.13)	84.17 (5.43)	90.96 (5.52)

Table – 3 presents results of ANOVA and pairwise Tukey test to determine the significance of difference in means in fitness values achieved by three algorithms in specified number of iterations. ANOVA test results (see Table 3) indicate that there is significant difference in means of all the three algorithms at the chosen $\alpha = 0.05$ level. Pair wise Tukey test (Table 3) and Table 2 show that for all the problems, QEA-C-VN (3) is significantly better than vQEA (2). Further, QEA-C-VN (3) is significantly better than cQEA (1) on all the Knapsack problems. However, the difference between 3 & 1 is not significant for MMDP, but 1 is significantly better than 2 on MMDP. Further 1 is better than 2 on Knapsack with size 100, but difference is not significant for the other two instances of the Knapsack problem.

Table 3. Statistical Significance on fitness value

Problems	ANOVA	Pairwise Tukey Test		
	P Value	3 & 1	3 & 2	1 & 2
MMDP	**0.000**	0.945	**0.001**	**0.000**
Knapsack (100)	**0.000**	**0.000**	**0.000**	**0.013**
Knapsack (500)	**0.000**	**0.000**	**0.000**	0.970
Knapsack (1000)	**0.000**	**0.000**	**0.000**	0.847

3. CONCLUSIONS

The experimental testing has shown that Cellular model improves the performance of QEA in comparison to other models on Massively Multimodal Deceptive Problem and some Knapsack problems. Thus, the contribution of this work is two folds viz., first is the critical examination of the population models employed in QEA, and second, the implementation of QEA on the Cellular Grid for fair comparison of the effect of all the three population models on QEA.

4. REFERENCES

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