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An Enhanced Quantum-inspired Genetic Algorithm with Artificial Entanglement: Analysis of its Search Behavior and Potential Applicability

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***Abstract*—In this paper, we present an approach, which is a correlation policy that demonstrates a potential of previously proposed artificial entanglement (AE). This said potential, is the ability to solve additional problems that exist in heuristic search algorithms such as the weakness of bit representation for the sequence of real numbers. Based on and adhering to the concepts of quantum entanglement, AE has a wide degree of freedom where its correlation and rotational behavior can be freely defined, be it simple or sophisticated for an approach from different angles towards the global optimum. A particular sample case of Schwefel function is selected and results are obtained and discussed.**

Keywords—quantum computing, genetic algorithms, numerical optimization, artificial entanglement, correlation.

I. Introduction

Quantum-inspired evolutionary computation (QiEC) has received a renewed attention as an emerging field due to its promising results in recent researches such as eQiGA [1] and rQEA [2]. While the prime reason behind the QiEC's success is because of the superposition of states due to probabilistic representation, enhanced quantum-inspired genetic algorithm (eQiGA) by the authors at Choy, C.K. et al (2014) has shown significant improvement over existing methods by further tackling the fundamental problem of heuristic search which is the exploration and exploitation dilemma. Instead of having adaptive search that incorporates both exploration and exploitation at the same time, two schemes were introduced that have distinct behaviours of explore and exploit. Its efficacy is tested with a pseudo-mechanism that bridges between the behaviours as a simple way to switch schemes and as a result, significant test scores were reported and analysed. This work emphasizes on exploring the potential of AE, with minor focus on performance.

II. Binary Representation of Real Values

Binary encoding has been long used since the introduction of GA for its robustness in representing a solution either in the form of a matrix or real values, and effectiveness when used with the genetic operators such as crossovers and mutations. Quantum-inspired evolutionary computation is similar to estimation of distribution algorithm (EDA) as both used probabilistic representation for their individuals in the population. By this definition however, to obtain a readable solution from the set of probabilities, one has to perform sampling or measurement on the individual which generates a string of binaries depending on the number of samplings.

As a solution candidate is represented by binary, it can be said that this kind of representation is still vulnerable to a number of weaknesses. One of which is the sequence of numbers. At certain points, there are cases where a real value represented faces difficulty in going to the next sequence regardless of direction whether increment or decrement. For example, given the real value range of $0 < x < 10$, it is likely that it is very difficult to decrease the value from 5.00 to 4.98. Even if the decrement value is small, this problem occurs because the hamming distance is too large. An example of the update required can be observed in Figs. 1 and 2.

1	0	0	0	0	0	0	0

Fig. 1. A sample binary string that represents the number "5.00" based on the value range.

0	1	1	1	1	1	1	1

Fig. 2. A sample binary string that represents the number "4.98" based on the value range.

By observing the figures, we can see that the hamming distance between the two values is actually eight for just a small decrement, this was referred as a "hamming wall" [3]. Therefore, a typical mutation scheme may face an issue as the update is usually minimal. Although this weakness was addressed since 1947 by Frank Gray, and hence, it is easily solved with the introduced Gray code. However, the Gray code is defined as a "reflective binary code" and there were few disadvantages: difficulty in arithmetic logic units, and requirement of additional encoding and decoding.

III. Artificial Entanglement

AE is designed based on two principle concepts of actual quantum entanglement: correlation and rotational behavior. To say that the design flawlessly matches the concepts may appeared to be far-fetched because in actual entanglement, the change of value of entangled particles occurs instantly when the value of any of the entangled pair is observed. This is dubbed by Albert Einstein as “spooky action at a distance” where the change occurs equally fast no matter how far the pair are separated away. However, there is no evidence that information actually travels between them. Whilst it is not possible to replicate the phenomenon, the concept is brought into conventional computing as a sequence of consequences. Details of the mechanism is described in [1].

IV. CORRELATION POLICY

A correlation policy defines the correlation between the original Q-bit and entangled Q-bit. It acts as a transformation gate when the entangled Q-bit is formed, generating a correlated value with the original. As AE does not reflect the true entanglement phenomenon, correlation policies can be defined with wide degree of freedom which further encourage unique approaches towards the optimal solution from the original standpoint. The aim of such policies is not just about pure performance but also to solve additional prominent issues as well such as the one mentioned in Section II. For this, we propose a simple policy for an initial start which is discussed in the next section.

V. EXPERIMENT: A SAMPLE CASE AND RESULTS

Consider the following case; in a numerical optimization, we have *n* dimensions for the variables in every individuals or chromosomes. As with the previously mentioned probabilistic representation, considering the algorithm is built with object-oriented paradigm where each chromosome is considered as an object, and each not only contains the set of probabilities but also the last observed solution, as a reference for the proposed policy. For example, naturally the true state of the chromosomes is illustrated as in Fig. 3 where each Q-bit consists of a set of α and β probabilities where α is the probability of being “0” and β is the probability of being “1”.

Hence from that, the correlation policy is applied upon the entangled Q-bits with reference to the last observed solution of the original Q-bits. The proposed policy begins by first randomly sample a dimension (of the referenced last solution). With the sampled dimension such as in Fig. 4, the policy examines the binary string from left to right and note every “1”s it sees. From the most front “1”, begin counting the number of “0”s that follows. If there are 2 “0”s, the position of the wall is assumed. A simple illustration that describes how it would look like can be seen in Fig. 4.

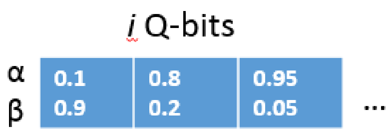

Fig. 3. An example of a chromosome with a set of *n* dimensions as variables for a problem domain

Fig. 4. An example of a sampled dimension and the position of a “1” being examined to assume the hamming wall

Once the hamming wall is identified, the same position is assumed for all other dimensions and the α and β beginning from the targeted “1” onwards are flipped. For testing purpose, we consider the Schwefel function, f_{Sch}. Algorithmic parameters from [1] are employed and the test function is defined as

$$f(x) = 418.9829(n) - \sum_{i=1}^{n} x_i \sin\left(\sqrt{|x_i|}\right), \quad (1)$$

where $-500 < x < 500$. The global minimum value is 0.0 at $(x_1, x_2, x_3, x_4 \dots x_n) = (420.9687, \dots, 420.9687)$. Convergence or termination point is set to $f(x) < 0.02$ and maximum function evaluations as 100,000. Results of with and without the proposed policy are shown in Table I. The symbols in Table I: m. and **σ** represents mean and standard deviation of function evaluations respectively, and r. is the number of successful convergence out of 100 trials.

TABLE I
EXPERIMENTAL RESULTS FOR SCHWEFEL FUNCTION (1)

		m.	**σ**	**r.**	**m. ending fitness**
f_{Sch}	**eQiGA [1]**	36684.4	40321.1	72/**100**	0.881
	eQiGA2	21418.0	13607.0	100/**100**	0.016

VI. DISCUSSION AND CONCLUSION

Based on Table I results, eQiGA2 which represents the current proposed method, has clearly achieved full convergence whereas eQiGA was unable to converge 28% of the time, out of 100 trials. It was observed that all the cases in those 28% were due to eQiGA facing the issue as mentioned in Section II. The proposed method is simple yet provides an opportunity for the solutions to make the “leap” within a reasonably short time and very minimal impact on the overall performance. This shows that the proposed method “eQiGA2” has demonstrated the applicability and effectiveness in resolving the issue with the proposed policy.

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