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Quantum Inspired Social Evolution (QSE) algorithm for 0-1 knapsack problem

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ABSTRACT

Social Evolution (SE) algorithm (Pavithr, 2014 [10]) is inspired by human interactions and their bias. Generally, human bias influences with whom individuals interact and how they interact. The individual bias may also influence the outcome of interactions to be decisive or indecisive. When the interactions are decisive, the individuals may completely adopt the change. When the interactions are indecisive, individual may consult for a second opinion to further evaluate the indecisive interaction before adopting the change to emerge and evolve (Pavithr, 2014 [10]). In the last decade, with the integration of emerging quantum computing with the traditional evolutional algorithms, quantum inspired evolutionary algorithm is evolved (Han and Kim, 2000 [2]). Inspired by Q-bit representation and parallelism and the success of the quantum inspired evolutionary algorithms, in this paper, a quantum inspired Social Evolution algorithm (QSE) is proposed by hybridizing Social evolution algorithm with the emerging quantum inspired evolutionary algorithm. The proposed QSE algorithm is studied on a well known 0-1 knapsack problem and the performance of the algorithm is compared with various evolutionary, swarm and quantum inspired evolutionary algorithm variants. The results indicate that, the performance of QSE algorithm is better than or comparable with the different evolutionary algorithmic variants tested with. An experimental study is also performed to investigate the impact and importance of human bias in selection of individuals for interactions, the rate of individuals seeking for second opinion and the influence of selective learning on the overall performance of Quantum inspired Social Evolution algorithm (QSE).

1. Introduction

Natural computing has taught us to think 'naturally' about computation and also to think computationally about nature [11]. Nature inspired computing has emerged as an efficient paradigm to design and simulate innovative computational models inspired by natural phenomena to solve complex non linear and dynamic problems. Some of the well known computational systems and algorithms inspired by nature are:

1. Evolutionary algorithms inspired by biological systems.
2. Swarm intelligence algorithms inspired by the behavior of swarm/group of agents.
3. Social and Cultural Algorithms inspired by human interactions and beliefs in the society.
4. Quantum Inspired Algorithms inspired by quantum physics.

Evolutionary algorithms (EAs) are search based stochastic optimization algorithms inspired by natural evolution and evolutionary biology. The main stream algorithms developed in this category are, Genetic Algorithms [12], Evolutionary Strategies [13], Evolutionary Programming [14] and Genetic Programming [15].

Swarm intelligence can be defined as [16] "a property of a system of unintelligent agents of limited individual capabilities exhibiting collective intelligent behavior". In general, a swarm can be considered to be a loosely structured collection of interacting agents [17]. Different swarm intelligence algorithms have evolved by mimicking the collective behavior of different social insects and animal societies. Some of the most popular swarm intelligence based algorithms include Particle Swarm Optimization [17], Ant Colony Optimization [18] and Artificial Bee Colony Optimization [19] inspired by flocking birds, ants and honeybees respectively.

Extending the swarm intelligence computational models to human interactions and beliefs in human societies, Reynolds [20] proposed the Cultural Algorithm and advocated that, "cultural evolution enables the societies to evolve or adapt to their environments at rates that exceed that of biological evolution based on genetic inheritance only" [20]. Inspired by human communities/

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societies and complex intra and inter society interactions, T. Ray and K.M. Liew [21] proposed Society and Civilization algorithm (SCA), which models the artificial societies with the leader and the individuals and their respective intra, inter interactions and migration among the societies.

Michael J. Maher analyzed different communication models and categorized them into seven level/patterns [28] such as Intrapersonal communication, Interpersonal communication, Small group communication, Organizational communication, Public communication, Intercultural communication and Mass communication. Aligning different communication levels into interactions, we can observe many interaction models in day to day life that may be represented in the following ways:

a. One-to-one: An individual interacts with one other individual in the society. This type of interaction model adopts an interpersonal communication pattern.
b. One-to-many: An individual interacts with many individuals in the society. In this type of interaction, an individual may interact with different individuals on different dimensions of the same one subject. This represents another variant of interpersonal communication pattern.
c. Many-to-one: Many individuals in the society interact with the one specific individual (leader) in the society. This type of interaction model is generally observed in public or mass communication pattern.
d. One-in-group: Here a group interaction is involved. However, in the group one individual is the most active participant, representing a small group communication pattern.
e. One-observe-group: The individual in question is observing a group of interacting individuals in the society and possibly interacting with them indirectly. In this interaction model, another variant of small group communication pattern is observed.
f. Self-Evolution: The individual explores based on personal or prior information, knowledge, bias and intuition, representing intrapersonal communication pattern.
g. Selective Learning: The individual explores and learns from historical information and archives. This model represents a variant of intrapersonal communication pattern, but in this model, the individual does not interact and communicate with one-self but selectively explores and learns from evolution's footprints.

In any of the above specified interaction models, an individual's actual selection of other individual or a group of individuals for an interaction may be based on available information, analytical capabilities, perceptions, opinions and biases. Generally, a Bias represents an “inclination or prejudice for or against one person or group” [29]. In statistical terms, it is “a tendency of an estimate to deviate in one direction from a true value” [41]. In practice, the decision-making process is heavily influenced by the assumptions and biases of the decision makers and these biases can be due to the limitation of cognitive abilities of the humans [42]. Levinson et al. [45] explains and explores the impact of interactional bias in human thinking and further remarks on the classic experiments conducted by Tversky and Kahneman on “Judgement under uncertainty” that, “despite the overwhelming everyday evidence to support basic principles of probability, people tend to follow other principles that yield incorrect conclusions” [45]. Though there are many different types of human bias [44], in evolutionary systems, along with other parameters, an individual's bias in selecting the individual for interaction (selective bias) plays an important role in the overall convergence.

In evolutionary algorithms, apart from selective bias, the acceptance of the outcome of an interaction to be decisive or indecisive may also be influenced by the individual's bias. In all the indecisive outcomes, the individual generally has the option of taking a second opinion. This behavior is observable in daily life. A recent survey on patient-initiated second opinions by Payne et al. [43] reveals that, about 10–60% of second opinions yield a major change in diagnosis and treatment and patients believe that second opinions are valuable. Similarly, in an another study, Second Opinion Consult clinic for surgical oncology [46] suggest that, about 24% of second opinion was different without and 7% was different with possible implications to the prognosis. In another study [47] on lung cancer patients, 91 out of 174 patients were benefited from second opinions. The above studies represent the importance of second opinions in medical conditions. The importance of second opinions has created a new opportunity for decision systems to evolve into recommender systems.

Modeling such human behavior, Pavithr and Gursaran [10] introduced the Social Evolution (SE) algorithm by incorporating human bias in selection of individuals for interaction and second opinion when the interaction's outcome is indecisive. According to [10], humans are intelligent and are capable of retaining information from indecisive interactions in their memory and may use this information for further evaluation of an interaction before adopting the outcome. The indecisive interactions may drive the individual to seek a second opinion and to build on the exchanged information from the previous interaction to progress towards decision making [10].

In the last decade, an interesting branch of evolutionary algorithms has evolved with the integration of the emerging quantum computing paradigm with the traditional evolutionary algorithms called quantum inspired evolutionary algorithms (QIEA) [2,3]. The QIEA has demonstrated its superiority over Canonical Genetic Algorithm (CGA) for combinatorial swarm optimization (HPSO and PSOPC) for real & reactive power dispatch problems [22], numerical optimization [50], clustering [48], image processing [49], routing [51], energy management [52], Graph coloring [56], Topology Optimization of Modular Cabled-Trusses [57] and many other applications.

Researchers have also attempted to integrate other nature inspired techniques with QIEA and have proposed hybrid quantum inspired evolutionary and swarm intelligent algorithmic variants to address complex problems. Some of the interesting hybridizations include, hybridizations between QIEA and CGAs [8], immune algorithms [23], particle swarm optimization [24], ant colony optimization [25], artificial bee colony optimization [26], hybrid quantum inspired GA and PSO [45], firefly algorithm [53], Glowwarm swarm optimization [54] P systems with active membranes [55] and many other variants.

Motivated by the philosophy of the social evolution algorithm and the success of the quantum inspired evolutionary algorithms and its hybridizations, in this paper, we propose a Hybrid Quantum Inspired Social Evolution algorithm (QSE), by integrating the Social Evolution algorithm of [10] with the Quantum Inspired evolutionary algorithm. The algorithm is experimented on the well known 0-1 knapsack problem with different control parameters to assess the impact and importance of human bias in selection of individuals for interactions, the percentage of individuals seeking second opinion and the influence of selective learning on the overall solution. The results indicate that, the bias in selection of individual for interaction and the second opinion process demonstrate the significance importance in overall convergence of the algorithm.

The performance of the QSE algorithm is also compared with binary version of the social evolution algorithm (adapted from [10] for this research) and the performance of the QSE algorithm is found to be much superior. Motivated by the results, the performance of the QSE is further compared with CGA, Binary Artificial