A Multiagent Evolutionary Framework for Complex Optimization Problems

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1. RESEARCH PROGRAM

Our research is within the subfield of multiagent systems for evolutionary algorithms (EAs). More specifically, we are interested in addressing two problems in multiagent-based EAs where agents (referred to as candidate solutions in EAs) are able to select services (i.e. pairs of evolutionary operators and their control parameters) to produce the high quality solutions for complex optimization problems:

- Automatically select evolutionary operators without prior knowledge;
- Adjust control parameters in uncertain environments.

To explain, candidate solutions to problems in EAs [1] play the role of individuals in a population. They produce offsprings by taking *evolutionary operators* (such as crossover and mutation) with user-specific *control parameters*. However, evolutionary operators and control parameters may vary for different problems. It is time-consuming to determine the operators and parameters by the trial-and-error procedure. In addition, the competency of operators may vary with generations. For example, crossover is often powerful in the earlier stage of EAs, but mutation is effective when the solutions are similar with each other in the later stage of EAs. The challenge of EAs is thus how to effectively select evolutionary operators and adjust control parameters from generation to generation and on different problems.

2. PROGRESS TO DATE

As the first step to tackle the above mentioned research problems, we look for a framework that reformulates the classical EAs as a multiagent system so as to take advantages of the developed multiagent technologies by the multiagent community. More specifically, we propose a novel multiagent evolutionary framework based on trust where each solution is represented as an intelligent agent, and the pairs of evolutionary operators and control parameters are represented as services. In our framework, the agents model the trustworthiness of the services, based on whether the agents' offsprings produced by using the services survive to the next generations, which represents the dynamic competency or suitability of the services from generation to generation and on particular optimization problems. The agents will then select the services with the probabilities correlated to the trustworthiness of the services.

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We begin with a novel insight that the intelligent agents are able to measure the dynamic competence of services and make decision autonomously in the process of EAs. The idea is inspired from the work of Jøsang et al. [3]. They define the trust concept and treat it as a dynamic value based on a collection of opinions that other agents hold about the service. We use the Beta distribution to measure the reputation score of each service on particular problems. In each generation, an agent selects a service to produce a new offspring agent, which is also a solution. The new offspring agent competes with other agents in the environment. If the offspring agent can survive to the next generation, it means that the service provides a positive outcome, otherwise, the service provides a negative outcome. The trustworthiness of services can be used to represent the competency of the services in producing positive outcomes. The larger number of outcomes a service can produce, the more suitable the service is to solve the given problem. Thus, agents in our framework model the trustworthiness of the services based on the number of positive and negative outcomes provided by the services in the past generations. The modeling results will be used by the agents to make decisions on which services to consume.

To date, we have defined the trust model for representing the dynamic competence of service. Assume s is the number of positive outcomes and f is the number of negative outcomes provided by a service S, formulated as follows:

$$\begin{cases} s = s+1 & \text{if } \vec{u}_{i,g} \rightarrow X_{g+1} \\ f = f+1 & \text{otherwise} \end{cases} \tag{1}$$

where $\vec{u}_{i,g} \rightarrow X_{g+1}$ means that the offspring $\vec{u}_{i,g}$ produced in the generation g by the service can survive to the next generation $g+1$. Whether $\vec{u}_{i,g} \rightarrow X_{g+1}$ is determined based on different methods in MOEAs [1]. The trustworthiness of S is then the probability expectation value of the Beta distribution, which represents the relative frequency of positive outcomes in future events [3].

$$T(S) = \frac{\alpha}{\alpha+\beta}, \quad \text{where} \quad \alpha = s+1, \ \beta = f+1 \tag{2}$$

A service is a tuple of a evolutionary operator and a set of segments for corresponding control parameters. The evolutionary operator can be any operator from a list of operators $O = \{O_1, O_2, \ldots, O_{|O|}\}$ proposed in EAs, where $|O|$ is the number of available evolutionary operators. Given a specific operator $O_k \in O$ in the service, there will be a set of control parameters $C^k = \{C^k_l | l = 1, \ldots, |C^k|\}$ associated with the operator O_k, where $|C^k|$ is the number of control parameters. Assume that a parameter C^k_l takes a continuous value in the range as $C^k_l \in [0,1]$. In order to effectively learn the performance of a control parameter, we divide the range $[0,1]$ into a set of q disjoint segments as $L = \{[0,\frac{1}{q}), [\frac{1}{q},\frac{2}{q}), \cdots, [\frac{q-1}{q},1]\}$. Thus, a service can be formally defined as a tuple (O_k, C^k) where $C^k = \{C^k_l | C^k_l = L(C^k_l), l = 1, \ldots, |C^k|\}$ and $L(C^k_l)$ is one of the segments in L for the parameter C^k_l.

We have developed a specified model to calculate the trustworthiness of evolutionary operators. In general, one operator is suitable for some specific types of problems, but may not work well for other types. Even for the same problem, the competency of the operator may vary in different generations. For example, the operator "DE/ran/1/bin" is suitable to multi-modal problems, which has slow convergency in the earlier stage but exhibits strong exploration in the later stage of EAs. Based on this phenomenon, the trustworthiness of the operator needs to reflect the varying competency of the operator under the condition where trust is hard to build up, but easy to lose.

The following function is used to combine the history information and current rating

$$\left\{ \begin{array}{lcl} s_g & = & (1 - T_{g-1}) \cdot s_{g-1} + T_{g-1} \cdot N_{g,s} \\ f_g & = & (1 - T_{g-1}) \cdot f_{g-1} + T_{g-1} \cdot N_{g,f} \end{array} \right. \tag{3}$$

where O_k is dropped out for clarity and T_{g-1} is the trustworthiness of operator O_k in generation $g-1$. Equation 3 has two important advantages. It does not have predefined parameters. Equation 3 also satisfies the above mentioned condition. When the trustworthiness of the operator in the last generation $g-1$, $T_{g-1}(O_k)$ is low, the operator needs more positive outcomes $N_{g,s}(O_k)$ to build up its trust in the current generation g. When $T_{g-1}(O_k)$ is high, $1 - T_{g-1}(O_k)$ is low, meaning that the less consideration will be given to historical information. The trustworthiness of the operator $T_g(O_k)$ will be easy to decline when the number of negative outcomes in the current generation $N_{g,f}(O_k)$ is large.

The trustworthiness of control parameter C^k_l associated with evolutionary operator O_k in the current generation g, denoted as $T_g(C^k_l|O_k)$, can be calculated in the similar way as calculating the trustworthiness of the operator O_k (Equation 3), by counting the numbers of positive and negative outcomes produced by the operator O_k with the parameter C^k_l, which are $N_{g,s}(C^k_l|O_k)$ and $N_{g,f}(C^k_l|O_k)$ respectively.

After having the trustworthiness of the evolutionary operator O_k, which is $T_g(O_k)$, and each control parameter C^k_l given O_k, which is $T_g(C^k_l|O_k)$, we can then compute the trustworthiness of the service (O_k, C^k) by assuming the control parameters are independent, as follows:

$$T_g(O_k, C^k) = T_g(O_k) \cdot \prod_{l=1}^{|C^k|} T_g(C^k_l|O_k) \tag{4}$$

In our framework, agents select services based on the computed trust results of the services. In order to balance between exploitation and exploration, services are selected in a probabilistic manner where the probability for a service to be selected is proportional to its trust. More formally, there are $\sum_k^{|O|} |C^k| \cdot m$ services in total because there are $|O|$ evolutionary operators, each operator O_k is associated with $|C^k|$ control parameters, and each parameter is represented by one of the q value range segments. The probability for service (O_k, C^k) with the trust $T_g(O_k, C^k)$ in the current generation g to be selected in the next generation $g+1$ is:

$$p(O_k, C^k) = \frac{T_g(O_k, C^k)}{\sum^{\sum_k^{|O|} |C^k| \cdot m} T_g(O_k, C^k)} \tag{5}$$

To demonstrate the effectiveness of the proposed multiagent framework, we select the multiobjective optimization problems (MOPs) as a case study. Experiments carried out on 35 benchmark MOPs confirm that our framework significantly improves the performance of the classic multiobjective evolutionary algorithms (MOEAs), including NSGAII, SPEA2 and MOEA/D, and outperforms the other three adaptive evolutionary approaches, including CMA-ES [2], SaDE [4] and CoDE [5]).

3. FUTURE RESEARCH

Our current research has two major contributions. The fist one is a multiagent-based evolutionary framework to reformulate EAs. In such a framework, a novel trust model is proposed to effectively select evolutionary operators and adjust control parameters (represented as services), for solving complex optimization problems (such as MOPs).

For future research, we will examine our framework in a distributed setting where only partial (local and neighboring) information about the outcomes of services is known to agents, towards the development of a distributed multiagent framework. The purpose of doing so is to adapt to the environments of the real world problems that are often very large and involve much uncertainty.

We will also explore the emerging application areas where our multiagent evolutionary framework can be applied to. Particularly, we will look into the problems in vehicular ad-hoc networks where vehicles represented by autonomous agents can communicate and share real-time traffic condition information so as to effectively navigate through the traffic. One such problem is the optimization of multiple objectives such as travel length and travel time. The complexity of the problem lies in its dynamic and large-scale properties. Another problem is related to message propagation among vehicular agents in the networks. Reliability of relaying nodes and the scalability of message propagation are the major concerns. By investigating these problems, the multiagent evolutionary framework will also be improved.

4. REFERENCES

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