Evolutionary Computation as a Form of Organization

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Abstract

Traditional areas of application of genetic algorithms (GA) are engineering and technology. Success of genetic algorithms there is well known. This paper explores the use of genetic algorithms as models to influence the design of organization. In particular, we outline the concept of evolutionary organization process based on two recent cases: the Teamwork for a Quality Education (TQE) and Free Knowledge Exchange (FKE) projects. The distinguishing feature of both projects is that computational evolutionary processes influence the organizational environment, providing the structure of interactions of people and facilitating their communication. In both cases, the organizational structure and people become directly involved into the evolutionary process integrating the power of evolutionary computation with the competence of participating human beings.

1 INTRODUCTION

Traditionally, evolutionary computation (EC) is considered separately from the organizational environment in which it operates. The organizational environment provides the problem to be solved and the fitness criteria of solutions. As a result of EC execution a population of good-enough solutions is created that feeds back into the environment. In this mode of operation, EC does not influence the structure of organizational environment from which it is invoked. Instead, it serves just as a functional unit of a fixed structural mechanism. However, if we look beyond one run of the EC process, the organizational environment has people who make changes to the problem and the fitness function. This can be viewed as another process of evolution: the evolution of human ideas or memes (Dawkins, 1976). Intuitively, the two processes of evolution, computational and human, have the same nature. Several authors suggested that genetic algorithms model human innovation (Goldberg, 1983; Holland, 1995; Goldberg, 2000). If so, the efficient and convenient interface between the two might speed up the evolution of the whole human-computer system. This paper considers two applications which provide such an interface, creating a fusion of computational evolution and the evolution of human thoughts. Such hybrid evolutionary process is interesting as (1) a method of studying innovative behavior of humans, (2) a natural method of embedding the competence of human users into an evolutionary procedure, and (3) an organizational method to improve the innovation ability of a group of people.

In this paper, we consider two applications of GA principle for social organization. The first project "Teamwork for a Quality of Education" (TQE) is a method to organize an educational process after the model of a genetic algorithm. The second project is "Free Knowledge Exchange", the web-based virtual organization that uses a human-based genetic algorithm (HBGA) (Kosorukoff, 2001) for its internal knowledge management and innovation.

2 TEAMWORK FOR A QUALITY EDUCATION (TQE) PROJECT

The TQE project was an application of the basic concepts of a genetic algorithm to create a more efficient educational environment (Goldberg, Hall, Krussow, Lee, & Walker, 1998). It introduced teamwork and design across the curriculum enlivened by a spirited, yet friendly competition among teams. It also defined the principles, projects, and the rules of the competition.

TQE is a competition of student-led teams, each team consisting of freshmen, juniors, and seniors together with faculty and staff advisors. Among TQE principles, the following three are most important for our analysis:

- **Pervasive Teamwork** To achieve higher quality delivery of engineering education, integrated teams should be employed throughout the engineering academy as they have been employed in industry.

- **Friendly Competition Among a Population of Teams** Participation and excellence should be driven by a friendly competition among a population of teams to win team awards based on excellence in academics, projects, and other categories.

- **Multiobjective evaluation** Each team is charged with obtaining the highest quality education possible for its members, and this goal is actuated through the series of competitions in three broad categories: (1) academics, (2) service and design, and (3) summer job placement.

TQE provides participants with a structure of interaction built upon the principles of a GA. In the common academic approach, faculty, staff, and students are like billiard balls that collide with one another when a course, advising episode, or other event calls for it. Under TQE program, the same collisions would take place, but the individuals would also be supported by a quasi-permanent interpersonal infrastructure of teamwork (Goldberg, Hall, Krussow, Lee, & Walker, 1998).

Additional information can be found elsewhere (Goldberg, Hall, Krussow, Lee, & Walker, 1998), but for the purpose of this paper the key thing to keep in mind is that the TQE was conceived partially because of the second author's experience with GAs. In other words, the very notion of a population of teams, a competition, a fixed (and multiobjective) "fitness function" were drawn from the example of GAs. Additionally, it was assumed that teams would emulate one another, thereby promoting a kind of selection and crossover. It was also assumed that a team member would spontaneously generate new and useful ideas, a kind of smart mutation.

While the common academic approach is oriented toward the development of the individual abilities of a student, TQE emphasizes the development of cooperative skills. Individual grading, the fitness function of usual education, is augmented by team grading, so the educational process optimizes the performance of a team rather than the peak performance of an individual. This produces diverse teams capable of solving tasks the complexity of which is beyond abilities of an individual specialist.

Table 1: Correspondence between elements and procedures of GA and TQE

GA	TQE
Gene	Member
Chromosome	Team
Population	Population of teams
Fitness function	Judging + grades
Generation	Semester
Initialization	Team formation
Selection	Team competition
Crossover	Team swaps + informal exchange
Mutation	New idea of a team member

A detailed description of the results of the TQE pilot project is beyond the scope of this treatment. Student feedback was generally good though the course required a substantial workload for the credit given. Detailed description of the results with the program is available elsewhere (Goldberg, Hall, Krussow, Lee, & Walker, 1998). Here we concentrate on the GA-connection.

The TQE project was inspired by a genetic algorithm, and there is a strong correspondence between its concepts and the concepts of a GA. This is represented in table 1

Most of the table is self-explanatory. New idea creation by a team member is analogous to a mutation of one gene, which is a team member in this case. The correspondence between TQE and GA procedures is pretty strong, except for the following two differences: crossover and reproduction operators.

The usual kind of GA crossover is difficult to apply to a team of people, because team members unlike genes have their own preferences and desires. Therefore, we cannot just swap members randomly between two teams. The practice of team swaps is tightly connected with the willingness of particular members to change their team, and usually this process happens actively only at the initial stages of TQE. After the teams become more or less solid, crossover rarely happen, so its combinatorial potential cannot be fully utilized.

Fitness-proportional reproduction is another problem in TQE. If some genotype is fit in GA we can easily reproduce and make several copies of its genes. It is clear that we cannot clone people of the fit team in the same way.

Concluding this section, we note that generally TQE is a working method of organization built after the GA model with some modifications reflecting social specifics of this project.

3 FREE KNOWLEDGE EXCHANGE (FKE) PROJECT

The Free Knowledge Exchange (FKE) project introduces the concept of evolutionary knowledge management based on concepts of GA. It used a human-based genetic algorithm (HBGA) for the task of collaborative solving of problems expressed in natural language (Kosorukoff, 2000a). It was created in 1997 for a small organization with the goal of promoting success of each member through new forms of cooperation based on better knowledge management. Currently it is a virtual internet community of more than 500 people from 92 countries. The FKE website www.3form.com evolves solutions to the problems of its participants in 7 different languages. It is supported by advertisement and allows anyone to join this community through the web and use it without a membership fee.

The FKE project explores evolution of natural language strings to arrive at better answers to the problems submitted by its members. It organizes individuals into collaborative community and uses their ability to perform intelligent crossover and selection operators on existing knowledge.

The idea of knowledge evolution in the most explicit form was suggested by Richard Dawkins (Dawkins, 1976). Evolution of natural language messages was explored in neuro-linguistic programming (Bandler & Grinder, 1976) and studied in the evolutionary theory of language (Pinker, 1998). Some web projects implicitly use evolution of messages to stimulate creativity, and the most relevant example is the Global Ideas Bank (GIB). Its main idea is collecting more successful and humane ways of doing things, and then re-presenting them in new mixes and matches, the accumulation of systems and arrangements that work a little better (Eno, 1998).

FKE makes the evolution of messages systematic and explicit using the framework of evolutionary computation. The four main ideas and their sources are shown in table 2: human interaction, emphasis on recombination, using natural language as a genotype, and diploidy.

Table 2: Main ideas behind FKE and their sources

Idea	**Source**
Human interaction	IGA
Natural language as a genotype representation	Meme theory by Dawkins
Emphasis on Recombination	GA
Diploidy	Creative questioning

The idea of human interaction came from interactive genetic algorithms (IGA) that introduced human evaluation interfaces in evolutionary computation. Human-based genetic algorithm (HBGA) used in FKE is basically an IGA combined with human-based innovation interfaces (crossover and mutation). In comparison with a typical interactive genetic algorithm using only human judgment (Herdy, 1996; Takagi, 1998), HBGA enjoys a balanced approach allowing and encouraging both convergent and divergent thinking of participants in the form of evaluation and recombination, correspondingly. This is accomplished by selecto-recombinative interfaces, where a person can perform selection or evaluation or both, based on one's preferences at the particular moment.

The use of natural language as a genotype representation was inspired by meme theory (Dawkins, 1976). It can be said that natural language strings have a tight linkage of building blocks, since in the most frequently used patterns of language their constituent parts tend to be located close to each other. Thus our natural language by itself has a good encoding for the purpose of genetic algorithm. We can hypothesize that the structure of language has itself evolved to allow this tight linkage of building blocks. Such a structure makes the evolutionary method of natural language processing efficient.

The emphasis on recombination is the main feature of GA. From an EC point of view, online interfaces of Global Ideas Bank are built on selection and mutation. They show ideas one at a time and allow users to evaluate them, to add new ideas and comments. Human-based mutation happens when one idea inspires another, and the result is submitted back to the ideas bank. This mechanism of evolution produces incremental continuous improvement, but lacks efficiency without recombination operator (Goldberg, 2000). The FKE project puts much emphasis on the process of recombination as do many GA implementations.

Table 3: An example of evolved answers in FKE

Q	How do you know that you are in the right career to really exceed in life and to do well overall?
18	You are in the right career if you wake up excited to go to work.
12	You need to feel it. If you're enjoying yourself, nothing else matters. As long as the money is enough to live by, you're fine there.
12	Rely on your intuition and senses. It should feel good to be in the right carreer :-)
11	You are in the right carreer if you wake up every day and can't wait to get to work. You spend all day doing what you love and then when its time to go home you really don't want to.
8	What is the definition of the right? If people want, then they can do anything and enjoy doing it. Nobody preassigns you from the birth to be a cook or a janitor, it is a choice which is made based on the life experience and the environment.

The use of diploidy came from creative questioning method (Ray & Myers, 1989). It assumes the separation of messages into the two classes: problems and solutions. After such a separation, we can evaluate the fitness of each solution for a particular problem, not just evaluate if some message is a good idea in general (the case of GIB). FKE divides all processed text strings into the two mutually exclusive classes: problems and solutions, by analogy with female and male distinction. This distinction creates two levels of co-evolution in FKE, each having the same recombination methods, but different methods and criteria for selection. The interplay between problems and answers in the FKE create an effect similar to the effect of creative questioning method.

Here we draw several examples that were evolved in the system. Table 3 shows the question having the highest fitness at the time of writing this paper. Answers are ordered according to their fitness which is shown in the first column of the table.

Table 4 shows another example clarifying the meaning of word "knowledge" in FKE. Questions about word definitions are common in FKE. One of the extentions of the projects suggested by its participants is to create a self-maintaining web dictionary evolving with the language itself.

Table 4: Word definition question

Q	What is knowledge?
4	Approximation of the outside world in our local observable vicinity. It is usually expressed in some alphabet of a limited size and doesn't approximate well beyond the local limits.
4	Knowledge is our personal extrapolation of information. Our minds take in information (or data) and spew out knowledge – even when we're wrong.
3	Knowledge is information valuable for us, that we gather, select and generalize throughout our life.
3	Something that keeps us from making the same errors twice.
3	Something very powerful and hard to attain. It is knowledge about things as they are or reality. With the correct knowledge almost everything is possible.

The selection process in FKE is delegated to its participants as in interactive genetic algorithms (Takagi, 1998), but processing of the individual evaluations is different. The system acts as a mechanism that collects, processes, and integrates the individual selections made by humans. We assume that humans are error-prone and consider them as unreliable classifiers, so the main purpose of the whole classification system is to minimize the overall error of classification. This purpose can be achieved by different decision-making mechanisms: ensemble averaging, arcing and boosting, or multi-stage classification (Kosorukoff, 2000b).

The selection of problems is performed according to their importance, based on expressed interest of participants in each particular problem. This measure of fitness based on the summed interest of all participants is used to include a problem into the generated web pages shown to people. This process happens in interfaces of HBGA, which generate the interactive WWW pages dynamically. Roulette wheel selection method is used for this purpose. In this way, the problem in which many people are interested will appear in the interfaces more frequently. The frequency of appearance of the particular problem in the interfaces and in dynamically generated WWW pages can be thought as a measure of attention the system pays to a particular problem.

The selection of solutions is performed according to their fitness in the context of specific problem. The method of cascading classification used for this pur-

Table 5: Self-awareness question

Q	What is a goal of FKE?
10	Allow people to cooperate effectively, and optimize the technologies of their interaction.
8	To help people
4	Help every member to achieve his/her goal, succeed in his/her enterprise no matter commercial or non-commercial. Success of every member makes our community more successful, and expands opportunities of other members.
4	Attract many people, provide them with effective technology of creative cooperation, test new ideas, develop and implement them, evolve fast to satisfy continuously changing demands of participants.
8	Attract people and increase creative potential of their community.

pose is based on creating an optimal classification structure from individual elements and letting solutions propagate through this structure. The method of structure assembly described in details elsewhere (Kosorukoff, 2000b) is based on evolving the representations of classifying networks with a genetic algorithm to achieve the minimum of the overall classification error.

The interesting thing about the FKE system is that it can define its identity, purpose, and evaluate its own performance, evolving the answers to the corresponding questions: what is FKE? what is the purpose of this community of people? is it useful? what is needed to make it better? By collecting this information the FKE system becomes 'aware' of what people think about it and which changes and improvements are needed. Most of these self-awareness questions appeared spontaneously in the process of evolution, as was the one shown in table 5.

These questions are circulating through the system, because participants express an interest to them. In this process the questions gather human opinions and evaluations, making the system aware of its purpose. Another self-evaluating question had the second best fitness at the moment of writing this paper. It is shown in table 6 with a list of the top 5 responses.

It this way, the FKE system becomes aware of its own performance. The satisfaction of people using the system is not a quantitative metric, but it agrees very well with the idea of this social system made for people. It can be said that FKE has no definite purpose. Human participants fill the purpose of FKE with their concerns and problems, and as long as these problems find solutions, the purpose of the whole organization is also fullfilled. To paraphrase Lao Tsu, FKE "has no purpose, but its purpose is fullfilled" (Tsu, 1972).

Table 6: Self-evaluation question

Q	What is your impression from this website?
10	It's very unique and really a good thing. This way people won't be afraid to ask.
9	This is a good way to continuously stimulate the thinking brain matters to keep one mentally fit
9	Could be helpful
8	The idea is quite smart. Here's hoping it can succeed, it's certainly got the potential
8	Interesting

Table 7: Correspondence between elements and procedures of GA and FKE

GA	**FKE**
Gene	Word of natural language
Chromosome	Text of question/answer
Population	Knowledge base
Fitness function	Human preference
Generation	Meta-interface cycle for solving a set of problems
Initialization	Solicitation of initial answers and migration of them from other populations
Selection	Ideas competition
Crossover	Crossover of answers
	Crossover of problems
Mutation	Random creativity technique

We still need to learn much about the mechanisms of evolutionary knowledge creation. The FKE project provides us with valuable data for this purpose: statistics about preferences of different people, methods of recombination and evaluation of natural language strings. What is clear by now is that FKE interfaces allow co-evolution of related populations of problems and solutions and this evolution results in selection of creative solutions and problems of interest. We believe that this is a sure way to new knowledge and understanding.

The correspondence between the FKE project and a GA is outlined in table 7. This table looks similar to the one for TQE. These are the same processes working in a different context. Different levels of evolutionary process are emphasized in these two models. Comparing TQE and FKE, we can see that the former model represents better the processes in the higher levels (group and participating individuals), while the latter pays more attention to the lower levels (individual problems and finding solutions to them). Nevertheless the very same methods work on these levels to achieve the goal of quality of education (TQE) and effective creative problem solving (FKE).

Additional information about FKE and HBGAs can be found elsewhere (Kosorukoff, 2000a; Kosorukoff, 2001), but for the purpose of this paper the important thing is that despite major representation and implementation differences, the core concepts of FKE are the same as those of early GAs and most of the theoretical concepts of GAs are applicable to the processes of knowledge evolution in FKE.

Table 8: Meta-structure of TQE

Organization component (human-based)	
Innovation component (human-based)	Selection component (human-based)

Table 9: Meta-structure of FKE

Organization component (computational)	
Human-computer innovation interface	Human-computer selection interface
Innovation component (human-based)	Selection component (human-based)

4 EVOLUTIONARY ORGANIZATION

In this section, we present the two projects described earlier as examples of a single *evolutionary organization process*. We identify its structure and components and try to find the areas where it has advantages over more traditional forms of organization.

Our case study has shown how similar the processes behind TQE and FKE are to the main concepts of genetic algorithms and evolutionary computation in general. This similarity makes the two projects like-minded, so we can view them as two social applications of evolutionary computation. However, although these projects use the principles of evolutionary computation, we cannot call them strictly computational, since they use human intelligence as part of them. We suggest the term *evolutionary organization process* to reflect the hybrid fusion of computational and human efforts.

Examples of the evolutionary organization processes that we considered so far had their own meta-structure. We call it meta-structure to distinguish from the structure of organization that is created. We separate meta-structure into three components: innovation (mutation and recombination), selection, and organization. Each component can be computational or human-based. TQE is an example of a process where all components are human-based. In FKE organizational component is computational, while innovation and selection components are human-based. In processes such as FKE, where both computation and human-based components are present, interfaces between them become an important part of computational component. The meta-structures of TQE and FKE are shown in table 8 and 9 respectively. Innovation and selection components can be represented by multiple agents, or their parts.

If we imagine the situation where organizational, innovation, and selection components are all computational, we will get a typical GA. This suggests that we can apply knowledge about the design of effective GAs to the engineering of the organizational component, which controls major parameters of the evolutionary process (such as selection pressure and probabilities of different kinds of innovation). However, we should always keep in mind the difference between the goals of evolution in a typical EC application and in evolutionary organization process: in the former case, the goal is fast convergence to the optimal design; in the latter case, the goal is an on-going process of innovation that should never get to a halt.

Now it is time to go from implementation to the results and discuss the actual system of organization that we get with evolutionary approach. Table 10 compares a traditional system organization with an evolutionary one.

Traditional organization is characterized by a structure that does not change often. The structure of organization is defined by its lines of communication. Usually the structure of communication is defined by rules, for example, “in case of computer failure call computer maintenance department”. As with a mechanical device, traditional organization assumes that each part will perform its function. In our case, a person in the computer maintenance department will answer the call and handle the problem. In this case, the communication process follows a fixed pattern or structure. Most violations of this pattern are harmful for the system as

Table 10: Comparison of traditional and evolutionary system of organization

Traditional organization	**Evolutionary organization**
Fixed form	Free form
Pre-designed based on static assumptions	Emerging and changing in the process: no apriori assumptions
Hard parts	Soft parts
Functional design: each part performs a specific pre-defined function	Organic design: multi-functional parts, not confined to performing a particular function
Emphasizes structure	Emphasizes process
Obligatory: based on contract	Participatory: based on contribution
Error correction: rejects spontaneous changes	Error utilization: uses spontaneous changes
Correctness based fitness	Achievement based fitness

a whole. For example, the failure of some part to perform its function often leads to the failure of the whole organization or at least some large part of the organization. Routing the problem to the wrong specialized unit will also result in functional failure. In these circumstances, reliability of parts and adherence to the established structure becomes the major priority.

When we consider an evolutionary organization, we notice many contrasts to the traditional one. There is no fixed structure. For example, we can not determine to which participant a particular problem will be routed in the FKE project. No matter who this person will be, his/her failure to solve the problem does not mean the failure of the whole system. Instead of a fixed structure of interactions, we have a stochastic process that recreates the new structure each time when communication is needed. It is easy to notice that in this case the relationship between structure and process is the opposite. Parts of the organizations are rather organic than functional, in other words they have ability to perform different functions in different time.

Since evolutionary organization process is built after the principles of EC, we can use the design principles of effective GAs to evolutionary organizations. However, we should keep in mind that the goal of evolutionary organization is different from the goal of standard GA. It is clear that fast convergence is not a goal of evolutionary organization. Convergence in the case of FKE would mean leaving a participant without any freedom of choice, and insisting that one 'correct' answer will work for the problem, in the case of TQE convergence would mean that all teams lose their identity, in the pursuit of perfection. That is not what we want in social environment. In this case any convergence will be premature, because the real-world does not stop there. A living organism which stops to adapt to changes will eventually die no matter how perfect it was before unless someone will take care of it. Convergence has little meaning in the living world, that is why traditional metrics of quality of the genetic algorithm based on time-complexity are often inadequate in these cases. For evolutionary organization we need an on-going evolutionary process, one that adapts easily to the changes of environment, never converging to the current best solution.

The experience with evolutionary organization process shows that the type of EC must correspond to the area of its application. Technical areas need competent GAs. Social areas need balanced or enlightened GAs (Goldberg, 1989). While competent GAs are designed to achieve fast convergence, balanced GAs can be designed to achieve innovation and creativity as a continuing process. Balanced GAs should be able to adapt to always changing environment, they should check if their assumptions about the world are still valid, and should be able to 'unlearn' them easily if they are not.

5 SUMMARY

The paper has considered two social systems designed explicitly with a GA in mind. The first of these organizes an educational process efficiently. The second promotes collaborative problem solving on the web. In both cases the inspiration and connection to GAs is clear. In the first, all functions of the system were performed by human beings. In the second, a mix of computational infrastructure and human interaction worked together. In both cases, interesting system behavior was observed and is continuing.

The paper continued by generalizing these types of systems and by calling such combines of human and computational power, evolutionary organization processes. The meta-structure of social organization processes was developed and more generally social organization processes were contrasted with traditional organizations.

While many if not most of the attendees of this conference are pleased to solve their organization's technical problems using the latest in genetic algorithms and evolutionary computation, this paper suggests that we may all have a larger role to play in the solution of our organization's organizational problems by appealing to our GAs and EC for inspiration, specific structure, and even population parameter settings. There is much work to do, but we believe that the examples and framework of this paper may be useful to these future efforts.

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