A Multilevel Cooperative Multi-Population Cultural Algorithm

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Abstract—A new architecture for Multi-Population Cultural Algorithm is proposed which incorporates a new Multilevel Selection framework (ML-MPCA). The approach used in this paper is based on biological group selection theory which aims to improve the capability of MPCA to tackle evolution of cooperation. A two-level selection process is introduced namely within-group selection and between-group selection. Individuals interact with the other members of the group in an evolutionary game that determines their fitness. If the group reaches a certain size, it splits into two daughter groups. We test our algorithm on CEC 2015 expensive benchmark functions to evaluate its performance. We show that our proposed algorithm improves solution accuracy and consistency. The model can be extended to more than two levels of selection and can also include migration.

Index Terms—Multilevel/Group Selection, Evolutionary Computation, Evolution of Cooperation, numerical function optimization.

I. INTRODUCTION

According to Darwinian principle of variation and natural selection, selection occurs at the level of individuals. Although Charles Darwin, in the “Descent of Man” wrote in 1871 that there can be no doubt that a tribe including many members who were always ready to give aid to each other and to sacrifice themselves for the common good, would be victorious over other tribes; and this would-be natural selection [1].

Evolutionary Computation (EC) is an optimization process inspired by the biological evolution. The evolution gives rise to biodiversity at all levels of biological organization, at the levels of species, individuals, groups etc. EC has not been used on many problems which require set of cooperative individuals to complete a task. Individuals cooperate differently and hence has different fitness values. The individuals with less fitness values will be discarded from the group irrespective of their contributions towards the performance of the algorithm. Some extensions to the basic evolutionary computational models to save such individuals from extinction from the population, were considered by Shelly and Wolfgang [2].

The success of cooperation is witnessed at all levels of biological organization. In nature individuals often group together into tribes into packs to cooperate and increase their chances of survival. Similar to the individuals, the groups that are fitter survive and create offspring’s, while those with lower fitness produce fewer offspring’s. This process can be compared to the human societies or animals or insect’s societies. Everyone is competing for food sources. The groups or societies that are fitter collect the food and survive on the other hand the groups or societies that are weak die from starvation.

Selection may occur at atomic or molecular level in cells, at the level of cells in individual, at the level of individuals in groups, at the level of groups in population, at the level of population in species, and finally at the level of species. A growing number of biologist have come to believe that group selection is the explanation even though it has been unpopular for long time.

In the group selection model, individuals are divided into groups and interact with members of the same group. Due to competition between the groups, cooperation emerges. The first group selection model was proposed in 1945 by Sewall Wright. Over the years, D.S Wilson was the main proponent of the idea of group selection [3]. There seems to be a renewed interest in the group selection approach these days. The present research in this area is about studying selection on multiple levels. The two group selection models proposed in this area are Sober and Wilson group selection model and Trauslen and Nowak’s group selection model [3]. In the first model the groups are mixed periodically during evolution, and in the later model, the groups are kept isolated. Hence the selection works differently for both the group selection models.

This work aims to study the simultaneous effect of natural selection on multilevel levels. We will extend the Trauslen’s group selection model rather than Wilson’s model. Our approaches will encourage cooperation in artificial evolution. We will use these approaches on multi-population cultural algorithm (MPCA) The approach used in this paper encourages the individuals to cooperate for the good of the group and in order to evolve into more powerful individuals.

The rest of the paper is organized as follows: Section 2 begins with the introduction of evolutionary algorithms and multilevel selection theories (MLS). Section 3 introduces the novel Multilevel Selection framework and explains the new algorithm in detail. Section 4 shows the experiments and results obtained. Section 5 concludes.
II. RELATED WORK

A. Evolutionary Computation

Evolutionary Computation (EC) is a set of algorithms that are inspired by the biological model of evolution and is a sub-branch of artificial intelligence which is used for meta-heuristic and stochastic optimization of complex problems. EAs are population-based algorithms incorporating the concept of evolution inspired from what is seen in nature. An evolutionary algorithm has set of randomly generated individuals called initial population. The evolutionary operators such as mutation and crossover generate a new population of individuals from the current population and the selection operator selects the best individuals for the next generation. This method is inspired by natural selection mechanism which state that the individuals that survive for next generation are the fittest individuals.

There are various algorithms that come under Evolutionary Computation, such as genetic algorithm, cultural algorithm, multi-population cultural algorithm, differential evolution, etc. Genetic Algorithm is a popular EA proposed by Holland. Cultural Algorithm is another EA developed by Reynolds. It incorporates knowledge to improve search mechanism. CA extracts knowledge in belief space during process of evolution and later uses that knowledge to direct the search processes. Multi-Population Cultural algorithm is another EA which can be seen as an extension of basic CA. In MPCA the multiple population are used to keep the population diversity and escape the local optimum regions [4].

Our proposed algorithm is pretty similar to the basic evolutionary algorithm approach in which the entire evolutionary dynamics is driven by individual fitness. Only individuals reproduce and generate offsprings. The only difference is that the different population of multi-population cultural algorithms will act as groups.

B. Multilevel Selection theory

When natural selection acts at the level of group during the process of evolution instead of at the level of individual that is said to be group selection. Group selection tries to explain the evolution of cooperation by introducing selection between groups. This is one of the mechanism by which we can evolve cooperation. This new perspective is now called Multilevel selection theory (MLS). The theory of group selection has been around since Darwin (1871). Group Selection explains the evolution of cooperation by introducing selection between groups [3].

Early researchers in this area debated that individuals would not altruistically sacrifice their fitness for the good of the group (e.g. Wynne Edwards 1962; Maynard Smith 1964). David Sloan Wilson has been a strong supporter of Group Selection approach since early 1990s. David Sloan Wilson and Elliot Sober in 1994 argued that similar to individuals the groups could also compete. Since 1990s group selection models have seen resurgence [1], [4]–[11].

Most of the multilevel selection models proposed for the evolution of cooperation, such as Wilson’s (1975) and Traulsen and Nowak (2006) models focus on how to propagate altruistic trait among individuals in a population [2], [6]. The groups in these models are regularly evaluated and formed. Groups with the more altruists will have higher fitness. The cooperative individuals in such groups will have higher probabilities to reproduce. Groups are temporary fitness-bearing entities, its not them but the individuals that are reproduced.

III. OUR MODEL

The inspiration of this research comes from group selection theory. The results provided by Banzhaf and Wu in [1], [12] on using group selection model in evolutionary algorithm motivated us to apply the multilevel selection approach in the population space of multi-population cultural algorithm. The group selection promotes the emergence of cooperation through evolution. We will use evolutionary algorithm to evolve cooperation. In this section we will show the multilevel selection framework.

A. MLS Framework

In our multilevel selection framework the population of individuals is subdivided into groups. The number of groups remain constant. The individuals of the group only interact with the members of the same group. Each group contains at least one individual. Each individual is assigned one strategy either cooperate or defect. Selection operates within groups and between groups. Within group selection favours individual with higher fitness in the group. Individuals therefore, compete within group. Between-group selection evaluates the performance of the group by seeing individuals of which group cooperate the best and selects that group.

The entire evolutionary dynamics is driven by individual fitness. Only the individuals in a group can reproduce. Groups can stay together or split or divide when reaching a maximum size. Groups that contain fitter individual reach maximum size faster and therefore they split more often. This concept leads to selection among groups, although only individuals reproduce in the population. These are the two levels of selection that we will study here.

Consider a population that is subdivided into groups. The fitness of the individuals is determined by a payoff from an evolutionary game. Members of the same group can interact with each other. Based on the Traulsen and Nowak group Selection model in [6], we will select the individual for reproduction from a group with higher fitness value. The individual will be selected for reproduction with the probability proportional to its fitness. The offspring generated will be added to the same group of the individual. When a group reaches its critical state, the group will split or divide into two daughter groups. The members of the group will be randomly distributed to the daughter groups. When a group divides another group is eliminated from the population based on its fitness value.

Any evolutionary game can be analyzed in our framework, but here we will focus on N-player Prisoner’s Dilemma (NPD). All the individual in the population will be assigned one
strategy cooperate or defect. Cooperators pay a cost $c$, and the other member that interacts with cooperator will receive a benefit $b$. Defectors pay no cost and give no benefit. Defectors benefit from cooperators present in a group. Cooperators get no help from defectors. In any mixed group, the defectors will have a higher payoff value. In homogeneous group, the cooperators will have a higher payoff than the defectors.

In our model, we will extend Trauslen’s group selection model instead of Wilson’s model. In this model, groups will not mix periodically during evolution. The group to be eliminated were selected randomly in Trauslen’s model. As an extension to this model, as proposed by Wu and Banzhaf, we will select the group to be eliminated inversely proportional to its fitness.

B. The Algorithm

As shown in Fig. 1, our algorithm has been designed based on the above framework. The step 1 of the algorithm is to randomly initialize the population with $N$ individuals each with unique ids and strategy either cooperate or defect. The population will be divided into local CAs or groups. The individuals in the local CAs or different groups are independent of each other. There is competition among individuals in the groups and this competition between the individuals of the group gives rise to cooperation among the individuals in the group. Each individual in the population is randomly initialized a strategy cooperate or defect.

$P$ - Generate Initial Population ($N$);
Initialize a strategy $C$ (Cooperate) or $D$ (Defect) to each agent;
$P' - $ Divide population equally among groups ($P$, $m$);
while Max Generation is not reached do
    Evaluate Fitness;
    for $i$=0 to $N'$ do
        $gn$ - Select group ($P$);
        $idv$ - Select individual ($P'$, $gn$);
        $idv'$ - Reproduce Offspring($idv$);
        Put back to group ($P'$, $gn$);
        if group size ($gn$) $> n$ then
            Split group($gn$);
            Remove group();
        end
        Update Local & Global Belief Space;
    end
    Output the best individual found so far;
end

Fig. 1. Pseudo-code of the ML-MPCA

The total population $N$ is then divided into number of groups $m$ or among different Local CAs. We first evaluate the individual and group fitness and start the reproduction process. In total $N'$ offsprings will be produced, where $N'$ is larger than or approximately two times the population size $N$. By doing this, cooperators get an opportunity to increase their frequency in the next generation. Then we select the parent individual for reproduction from the group with highest fitness value. The offspring generated will be put back into the same group ($gn$) from which the parent individual was chosen for reproduction.

Next step, we check if the group size of group $gn$ is greater than $n$, a predefined number, we split the group into two daughter groups. The members of the parent group are randomly distributed in the daughter groups. We select the group reversely proportional to the fitness to be eliminated from the population. This is done in order to maintain the constant number of groups in the population. After each iteration we update the local and global belief space.

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TABLE I
SUMMARY OF THE CEC 2015 OPTIMIZATION TEST PROBLEMS
IV. EXPERIMENTS

In this section, the experiments have been done to evaluate the effect of multilevel selection in optimizing the test functions. All the test functions used are minimal functions. Some functions are non-convex, and some are convex and are dimension wise scalable. The performance of ML-MPCA is evaluated in comparison with standard genetic algorithm (GA) and the multi-population cultural algorithm.

A. Representing Fitness Function

We compare the performance of our algorithm with standard genetic algorithm and MPCA and we will also study the performance of our algorithm in extending the evolutionary algorithms to evolve cooperation. Our study is carried out in context of n-player prisoner’s dilemma problem (NDP). We will analyze the individual and group level selection. In this game, N individuals are chosen randomly into m groups. Individuals in a group are assigned one strategy either cooperate or defect. The fitness function of the cooperators and defectors in group m is specified by the following equations:

\[
f(cm) = base + \left[ \frac{b(nq - 1)}{(n-1)} \right] - c \quad (1)
\]

\[
f(dm) = base + \left[ \frac{b(nq)}{(n-1)} \right] \quad (2)
\]

Here, base is the base fitness of the cooperators and defectors, m is the group name, q is the fraction of cooperators in group m, n in the group size, b and c are the benefit and cost of the altruistic act.

It can be seen from the fitness function that the cooperators have a lower fitness than defectors. Cooperators always have to pay a cost c and receives benefit from fewer cooperators than the defectors. Although the defectors dominate the cooperators inside the group but the groups with more number of cooperators will always outperform the defectors i.e. they will always have higher fitness. Here, the dynamics in the individual and group level selection drive the dynamics in different direction.

B. Experimental Setup

To test the performance of our algorithm, we have used CEC 2015 expensive benchmark functions in [13] which contain 15 functions. The test is carried out in terms of optimum solution after a predefined number of iterations. These functions are used in literature to evaluate the performance of the population-based methods. The first two functions are unimodal with one optimum, Multi-modal functions, hybrid functions and composition functions. The table 1 summarizes the 15 expensive benchmark functions on which we will carry out tests.

C. Evaluating performance of different Algorithms

We compared our results against Genetic algorithm and classic multi-population cultural algorithm using the mean fitness and standard deviation. The mean fitness value is mean value of the solutions got at the maximum generation in 100 runs and standard deviation is the standard deviation of the mean fitness. These are just the preliminary results and can be improved by varying the parameters like number of cooperators and defectors in the group, changing group size, varying number of groups, varying number of generations.

Here we assume asexual reproduction for our experiment and we have considered few parameters that are common while few were specific for each algorithm. Common parameters are maximum generation = 1000, population size = 100, total runs = 20 and number of groups = 10. Each group has 10 individuals in them and a local belief space which stores the best individual of the current generation. We have tested our algorithms 20 times on each problem and have noted the mean best value.

The experiments were done using Java programming language. Intel(R) Core(TM) i7- 2600s CPU @ 2.80Ghz and 8.00 GB RAM system was used for running the experiments.

The evaluation results are shown in table 2. The solutions of genetic algorithm and MPCA are taken from [14]. It can be seen from the results that ML-MPCA outperforms other algorithms on 9 out of 15 test functions. It works well on both hybrid and composite problems showing good results against 5 out of 6 problems. It also shows good performance for simple multi-modal functions.

As mentioned the results are preliminary and can be tested by changing the parameters which have a good chance of improving the results. The proposed system shows good results on complex problems rather than simple problems.

V. CONCLUSION

This paper implements a novel bio-inspired mechanism which is based on the modern theories of evolution to improve the performance of multi-population cultural algorithm. The effect of multilevel selection theory was considered in this proposed ML-MPCA algorithm. ML-MPCA divides the population into groups and apply social processes within and between groups.

ML-MPCA algorithm was compared with the original genetic algorithm and MPCA on CEC 2015 expensive benchmark functions. The experimental results show that ML-MPCA when compared to traditional MPCA and GA, is able to improve solution accuracy, is reliable, has fast convergence speed and outperforms other evolutionary algorithms investigated in this paper.

In the future work we plan to extend this model to more than two levels of selection and also include migration. We can study the change in the percentage of cooperators in the groups. Also, this model can also be extended to study the evolutionary transition similar to the work done by Wu and Banzhaf in [9].
## References


[5] D. S. Wilson and E. O. Wilson, “Evolution” for the good of the group”: The process known as group selection was once accepted unthinkingly, then was widely discredited; it’s time for a more discriminating assessment,” American Scientist, vol. 96, no. 5, pp. 380–389, 2008.


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### Table II

**Evaluation results on CEC’15 expensive test functions**

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