Non-genetic Transmission of Memes by Diffusion

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ABSTRACT

In recent years, there has been an increase in research activities on Memetic Algorithm (MA). MA works with memes; a meme being defined as "the basic unit of cultural transmission, or imitation" [5]. In this respect, a Memetic Algorithm essentially refers to "an algorithm that mimics the mechanisms of cultural evolution". To date, there has been significant effort in bringing MA closer to the idea of cultural evolution. In this paper we assess MAs from the perspectives of "Universal Darwinism" and "Memetics". Subsequently, we propose a Diffusion Memetic Algorithm where the memetic material is transmitted by means of non-genetic transfer. Numerical studies are presented based on some of the commonly used synthetic problems in continuous optimization.

Categories and Subject Descriptors

I.2.m [**Artificial Intelligence**]: Miscellaneous—*Evolutionary computing and genetic algorithms*

General Terms

Algorithms

Keywords

Cellular automata, Genetic algorithms, Optimization, Local search

1. INTRODUCTION

The theory of "Universal Darwinism" was coined by Richard Dawkins [5] in 1983 to provide a unifying framework governing the evolution of any complex systems. In particular, "Universal Darwinism" suggests that evolution is not exclusive to biological systems, i.e., it is not confined to the narrow context of the genes, but applicable to any complex systems that exhibit the principles of inheritance, variation and selection, fulfilling the traits of an evolving system. For example, the new science of memetics represents the mind-universe analogue to genetics in culture evolution that stretches across the fields of biology, cognition and psychology, which has attracted significant attention in the last decades. The term "meme" was also introduced and defined by Dawkins [5] in 1989 as *"the basic unit of cultural transmission, or imitation"*, and in the English Oxford Dictionary as *"an element of culture that may be considered to be passed on by non-genetic means"*. Although the definition of the word 'meme' has remained ambiguous and controversial in the field of Anthropology, the concepts and theories in the study of human culture and memetics are recently derived in the form of computational intelligence and then adapted into operational algorithms for solving real-world problems in the fields of arts, digital media, business, finance, science and engineering. Within this growing trend, which relies heavily on state-of-the-art optimization and design strategies, the methodology known as Memetic Algorithms is, perhaps, one of the most successful stories.

Inspired by both Darwinian principles of natural evolution and Dawkins' notion of a meme, the term "Memetic Algorithms" (MAs) was first introduced by Moscato in his technical report [12] in 1989 where he viewed MA as being close to a form of population-based hybrid genetic algorithm (GA) coupled with an individual learning procedure capable of performing local refinements. The metaphorical parallels, on the one hand, to Darwinian evolution and, on the other hand, between memes and domain specific (local search) heuristics are captured within memetic algorithms thus rendering a methodology that balances well between generality and problem-specificity. In a more diverse context, memetic algorithms is now used under various names including Hybrid Evolutionary Algorithm, Baldwinian Evolutionary Algorithm, Lamarckian Evolutionary Algorithms, Cultural Algorithm or Genetic Local Search. In the context of complex optimization, many different instantiations of memetic algorithms have been reported across a wide range of application domains [2, 7, 11, 18], in general, converging to high quality solutions more efficiently than their conventional evolutionary counterparts.

While GA tries to emulate biological evolution, MA is said to mimic cultural evolution. In what follows, we summarize and categorize Memetic Algorithms into different generations.

- **1st generation**: The first generation of MA refers to hybrid algorithms, a marriage between a population-based global search (often in the form of an evolutionary algorithm) coupled with a cultural evolutionary stage. This first generation of MA although encompasses characteristics of cultural evolution (in the form of local refinement) in the search cycle, it may not qualify as a true evolving system according to Universal Darwinism, since all the core principles of inheritance/memetic *transmission*, *variation* and *selection* are missing. This suggests why the term MA stirs up criticisms and controversies among researchers when first introduced in [5].
- **2nd generation**: Multi-meme [9], Hyper-heuristic [8] and

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Meta-Lamarckian MA [14] are referred to as second generation MA exhibiting the principles of memetic *transmission* and *selection* in their design. In Multi-meme MA, the memetic material is encoded as part of the genotype. Subsequently, the decoded meme of each respective individual / chromosome is then used to perform a local refinement. The memetic material is then transmitted through a simple inheritance mechanism from parent to offspring(s). On the other hand, in hyper-heuristic and meta-Lamarckian MA, the pool of candidate memes considered will compete, based on their past merits in generating local improvements through a reward mechanism, deciding on which meme to be selected to proceed for future local refinements. Meme having higher rewards will have greater chances of being replicated or copied subsequently. For a review on second generation MA, i.e., MA considering multiple individual learning methods within an evolutionary system, the reader is referred to [15].

- **3rd generation**: Co-evolution and self-generation MAs introduced in [17], [9] and [10] may be regarded as 3rd generation MA where all three principles satisfying the definitions of a basic evolving system has been considered. In contrast to 2nd generation MA which assumes the pool of memes to be used being known *a priori*, a rule-based representation of local search is co-adapted alongside candidate solutions within the evolutionary system, thus capturing regular repeated features or patterns in the problem space.

In the 2^{nd} and 3^{rd} generations of MA, it is worth noting that memes can be transmitted and selected by means of genetic or non-genetic transfer. In the former approach, memetic material is encoded into the genotype making use of crossover, mutation and selection operators to spread from one individual to another across generations. On the other hand, the latter approach considers a separate channel for meme transmission. Though it may increase the computational cost, non-genetic transfer of meme provides a more flexible mechanism for meme transmission and brings more interesting topics, such as the mutual influence between gene and meme evolution, to be be further discussed in Section II.

In this paper, we present a study on non-genetic transmission and selection of meme via diffusion. The paper is organized as follows. Section II discusses the forms of transmission mechanism in Memetic Algorithm. A memetic algorithm with meme diffusion (DMA) is then presented in section III. Section IV presents the numerical study on the search performance of DMA. Finally, Section V concludes with some recommendations for further research.

2. CULTURE TRANSMISSION AND SELECTION IN MEMETIC ALGORITHM

In this section, we focus on the 2^{nd} generation Memetic Algorithm which mimics the mechanisms of inheritance/memetic transmission and meme selection in their design. The general details of a 2^{nd} generation MA is outlined in Algorithm 1. The change from the 1^{st} to 2^{nd} generation MA lies in the additional meme selection process. To understand how a meme being transmitted and selected, one can refer to the corresponding models in gene evolution. A major difference that one tends to find is in the mechanisms of culture transmission, which is far more varied than gene transmission. Parent-child (vertical) transmission is present in both. Peer transmission (horizontal), for example, exhibits the exhibits the characteristics of cultural transmission, but is practically absent in genetics. The variety of cultural transmission mechanisms that exists bring about far more flexibilities than genetic evolution [3].

Algorithm 1 Memetic Algorithm (2^{nd} generation)

Generate an initial population
Initialize the meme pool
while Stopping conditions are not satisfied **do**
    Evaluate all individuals in the population
    Evolve a new population using stochastic search operators
    Select the subset of individuals, Ω_{il}, that should undergo the individual improvement procedure
    for each individual in Ω_{il} **do**
        Select a meme from meme pool
        Perform individual learning using the selected meme
        Proceed with Lamarckian or Baldwinian learning
    end for
end while

In the context of optimization, parent-child (vertical) transmission takes place only when the offspring is generated as two or more individuals (referred to as parents) mates. It is also noted that memetic transmission from parents to children may take place through genetic or non-genetic means, i.e., memes may or may not be encoded as part of the genotype. On the other hand, meme can transfer from one individual to another (horizontal transmission) at anytime throughout the life cycle of an individual, suggesting that this form of transmission mechanism may pose a greater impact on the distribution of memes in the population.

The inheritance mechanisms in multi-meme [9] and co-evolution [17] MAs are purely genetic as the memetic material is encoded as part of the genome, where the transmission of genetic and cultural traits is achieved only through the underlying alleles. On the other hand, hyper-heuristic [8] and meta-Lamarckian [14] model the mechanisms of non-genetic inheritance since the rule of inheritance is based on fitness of the memes in generating local search improvement. Despite these works, it is worth noting that there exists a plethora of non-genetic transfers, which may include migration, diffusion, direct teaching, and many others. For example, if a meme can be transmitted within a local vicinity, which is commonly referred as a *diffusion* process or on the other hand, an offspring might receive the meme directly from its parent as a result of *direct learning*.

To the best of our knowledge, till today little effort has been spent on studying the non-genetic transmission of meme in the context of evolutionary and memetic computation. It would be interesting to note whether by communicating with a large number of peers (individuals within the same population), learning would be more effective and beneficial than just inheriting directly from parents. In the sections that follow, we will demonstrate how such a form of learning can be mimicked in the context of evolutionary and memetic optimization. Various factors that affect the learning and selection process of meme(s) will also be discussed.

3. DIFFUSION MEMETIC ALGORITHM

In nature, both genetic and memetic transmission take place among individuals which are geographically near to each other, either physically or virtually. Cellular Genetic Algorithm (CGA) [1] mimics that behavior by using a decentralized structure where each chromosome can only interact (mate) with other chromosomes within a particular neighborhood (see Figure 1). In a CGA, each individual has its respective pool of potential mates defined by neighboring individuals; while at the same time, each individual serves as mates in multiple pools. In this way, one-dimensional (1-D) or two-dimensional (2-D) structures with overlapped neighborhoods are then used to provide a smooth diffusion of good solutions across the grid.

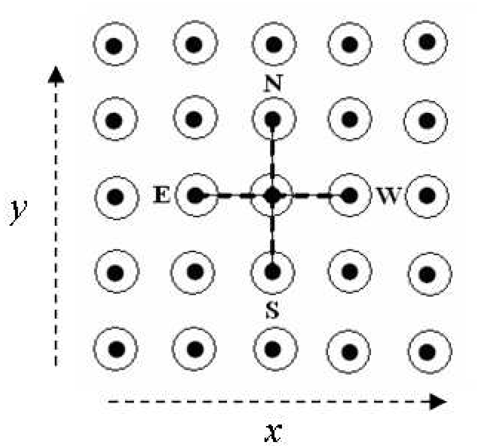


Figure 1: Neighborhood structure in Cellular Genetic Algorithm

Based on the structure of CGA, we introduce a Diffusion-MA (DMA) for studying the non-genetic transfer of meme in the context of evolutionary optimization. A 2^{nd} generation memetic algorithm with meme diffusion is outlined in Algorithm 2. In DMA, the population is organized on a two-dimensional grid of $WIDTH * \times HEIGHT$, each individual being located on a grid cell. The main difference between DMA and Cellular Memetic Algorithm is that individual may be associated or tagged with a meme that will be used to perform local improvement on it. In the first generation, the meme attached with each individual is randomly initialized. Note that individuals may also be initialized without any meme tagged to it.

Subsequently, the individuals undergo the evolutionary process. At each generation, individual in each cell of the grid mates with one of its neighbors to produce a new offspring. The mating neighbor is selected by means of natural selection, for example biased roulette wheel. The offspring then replaces the original parent. Subsequently, meme learning takes place to decide on the choice of meme that will operate on an offspring. The individual learning process is performed for every α generations, with each individual in the population refined by the meme associated to it. Here, α refers to the individual learning interval, which balances the degree of evolutionary and individual learning in the search.

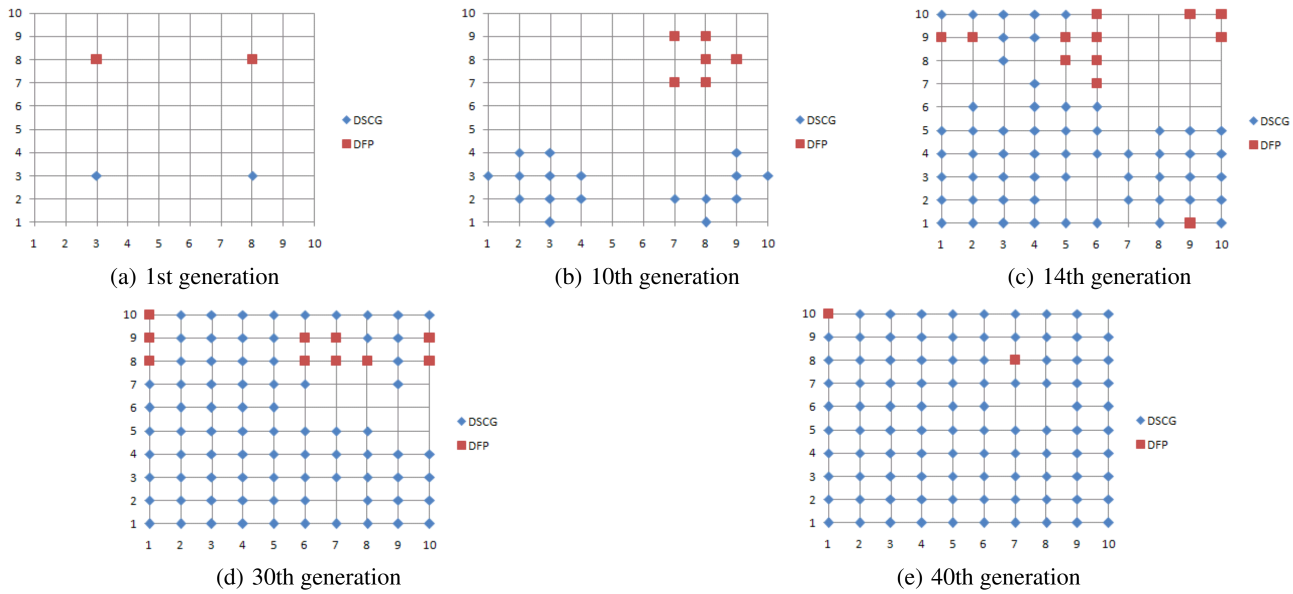
It is noted that in general, meme can either be inherited from its parent (parent-child transmission) or learned from other individuals in the population (peer transmission). In DMA, the offspring learns the meme from its neighbors in the grid instead of inheriting directly from the parents. Since meme information can only be transmitted from one individual to its neighbors, the process of meme transmission is achieved via "diffusion". Algorithm 3 illustrates how a meme associated with the offspring can be determined by learning from its neighbors based on some rewarding scheme. A possible instantiation of meme selection can be defined by the fitness of an individual's neighbors. For example, the reward of a meme defined by the average fitness of neighbors that shares the same meme is considered in Algorithm 3. Subsequently, memes having higher rewards are then equipped with greater chance of survival.

Algorithm 2 Diffusion Memetic Algorithm

```
procedure DIFFUSIONMA
    Initialize-Meme-Pool;
    pop = Create-Grid (WIDTH * HEIGHT)
    for x = 1 to WIDTH do
        for y = 1 to HEIGHT do
            initialize pop(x, y)
            pop(x, y).fitness = Evaluate(pop(x, y))
            pop(x, y).meme = Random-Meme;
        end for
    end for
    while termination condition is not satisfied do
        for x = 1 to WIDTH do
            for y = 1 to HEIGHT do
                /*Gene transmission*/
                parent1 = pop(x, y)
                parent2 = Select(Neighbors(x, y));
                child = Crossover(parent1, parent2)
                child = Mutate(child)
                child.fitness = Evaluate(child)
                /*Meme transmission*/
                child.meme = Meme-Selection()
                if (generation mod α = 1) then
                    /*Individual learning*/
                    child = Local-Improvement(child)
                    if childls.fitness > child.fitness then
                        replace pop(x, y) with childls
                    else
                        replace pop(x, y) with child
                    end if
                else
                    replace pop(x, y) with child
                end if
            end for
        end for
    end while
end procedure
```

Algorithm 3 Meme Selection

```
function MEME-SELECTION(neighbor-list)
    for all meme m in meme-pool do
        m.reward = 0
        m.count = 0
    end for
    for all neighbor n in neighbor-list do
        m = n.meme
        m.reward = m.reward + n.fitness
        m.count = m.count + 1
    end for
    for all meme m in meme-pool do
        m.reward = m.reward/m.count
    end for
    return meme with highest reward
end function
```



(a) 1st generation (b) 10th generation (c) 14th generation

(d) 30th generation (e) 40th generation

Figure 2: Memetic map across different search generations of DMA (DSCG + DFP) on 30D Griewank

4. EXPERIMENTAL STUDY

In this section, we present a numerical study to analyze non-genetic transmission of memes by diffusion in the context of 2^{nd} generation memetic algorithm. Particularly studies will be made based on the Diffusion Memetic Algorithm. Three commonly used continuous parametric benchmark test problems already extensively discussed in the literature are considered. The benchmark problems used represent classes of Multimodal and Epistatic / Non-Epistatic test functions. Table 1 tabulates the two test functions with their notable characteristics. Each run continued until the global optimum is found or a maximum of 300,000 function evaluations is reached. In addition, the algorithms terminate upon convergence when a fitness error of 10^{-8} with respect to the global optimum is reached.

In the present study, the Cellular GA parameters for all the algorithms are configured consistently with grid size of 10 x 10 real-coded solutions, Gaussian mutation and uniform crossover are used with probability settings of 0.03 and 0.9, respectively, while biased roulette wheel is used for selection. For individual learning procedures or memes, we consider the i) procedure of Davies, Swann, and Campey with Gram-Schmidt orthogonalization (DSCG) [16], ii) Davidon, Fletcher and Powell's Quasi-Newton Strategy (DFP) [4] and iii) the Simplex Method by Nelder and Meade (Simplex) [13] which are representatives of first and zeroth order exact individual learning methods commonly found in the literature. On all the CMA and DMA variants considered, the individual learning interval, labeled as α in Algorithm 2, is set to 10 generations, i.e., individual learning phase is applied for every 10 generations. In each individual learning phase, a maximum computational budget of 100 functions evaluations is used. For each experiment, the average of fifty independent search runs are presented.

4.1 Meme Diffusion in MA, DMA

In this subsection, we first demonstrate the idea of meme diffusion in the context of memetic algorithm. In particular, we illustrate the effect of using a non-genetic transmission of memes by diffusion based on the DMA when searching on the 30-dimensional Griewank problem. In this example, we considered a pool of two memes based on the local learning procedures DSCG and DFP. GA population is initialized with four individuals associated with a meme while all remaining individuals in the population do not associate with any meme. In particular, individuals at positions $(3,3)$ and $(3,8)$ of the grid are assigned with DSCG meme while those at positions $(8,3)$ and $(8,8)$ have the DFP meme (see Figure 2(a)).

Figure 2 illustrates the diffusion process of the memes at different instances of the DMA search, i.e., at generations 1, 10, 14, 30 and 40. It is observed that as the evolution begins, memes that are deem to generate better search improvements or solution qualities based on some reward metrics, are given higher chance of surviving, thus they spread or diffuse across its neighbours through the offspring, (see for example, Figure 2(b)). As the search evolves further, most cells in the grid are shown to have been infected with a meme at generation 14 (Figure 2(c)). In addition, it is noted that the DSCG meme are spreading faster than DFP since the number of individuals infected with the DSCG meme are much higher than those with DFP meme. This suggests the stronger local learning or refining capabilities of DSCG over the DFP meme on the problem of interest. Subsequently when most the cells have been infected with a meme, individuals in a neighborhood may be associated with different memes and these memes will have to compete for survival to take greater ownership of the entire grid (see Figure 2(d)). Weak memes will eventually fade away and may cease to exists due to their poor performance. Finally, at the end of generation 40, nearly all the cells in the grid are shown to have been infected by the DSCG meme (Figure 2(e)), demonstrating the greater efficacy of the DSCG over DFP.

4.2 First generation Cellular Memetic Algorithms

To begin we first present the search traces of the 1^{st} generation Cellular Memetic Algorithms (CMAs) when used to search on the benchmark problems in Figures 3 and 4. Note that the different CMAs presented are formed by a synergy of the canonical CGA and a meme. From the results shown, it is clear that no single CMA always performed best on all the two test functions. Even worst, some CMA is shown to perform poorer than the CGA on

Table 1: Benchmark functions used in the study (epi*: epistasis, mul*: multimodality)

Function	Range	Characteristics	
		Epi*	Mul*
$F_{Rastrigin}(\mathbf{x}) = 10n + \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i))$	$[-5.12, 5.12]^{30}$	none	high
$F_{Griewank}(\mathbf{x}) = 1 + \sum_{i=1}^{n} x_i^2/4000 - \prod_{i=1}^{n}\cos(x_i/\sqrt{i})$	$[-600, 600]^{30}$	weak	high

30D Griewank. This is as expected since it is generally acknowledge that culture evolution does not not always bring about fitness maximization as one wishes.

For example, Hughes [6] highlighted: *"on the average, the wealthiest Western European families in the 1600s had six children, reared four to adulthood, but only married off two per family (again on average). By circa 1700 Western Europe's elites had begun to reduce the very high death rates from which their infants and children traditionally suffered; but as death rates for the young fell, so did birth rates. Demographic contraction [among the elites] continued throughout the 1800s despite improved survivorship'*.

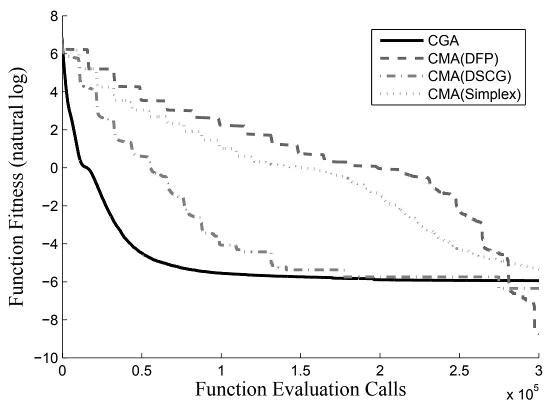


Figure 3: Search performance of CGA and CMAs on 30D Griewank

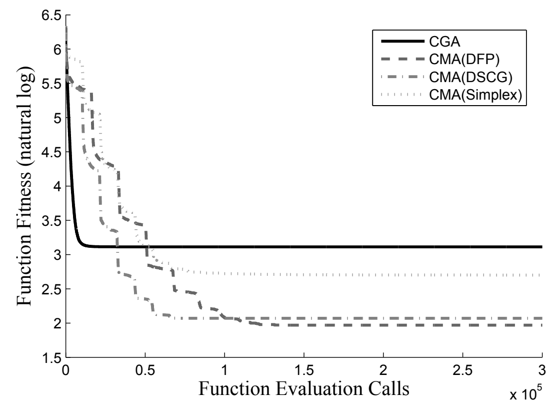


Figure 4: Search performance of CGA and CMAs on 30D Rastrigin

4.3 Benefits of Meme Diffusion

Next, we study the impact of using meme diffusion on evolutionary search performance by comparing the Diffusion Memetic Algorithm with 1^{st} generation Cellular Memetic Algorithms (CMAs), to determine whether the non-genetic transfer mechanism considered could translate to practical benefits in the context of optimization.

Here, we consider several instantiations of meme pools. This involves experimental studies on DMA with meme pool consisting of different combinations of meme pairs, i.e, DSCG + DFP, DFP + Simplex and Simplex + DSCG, and the combination of all three memes, i.e, DSCG + Simplex + DFP to search on 30D Griewank and Rastrigin functions. The search traces plotted in figures 5 and 6 indicate that both the DSCG and DFP memes spread faster than the Simplex meme, which explains why the search performances

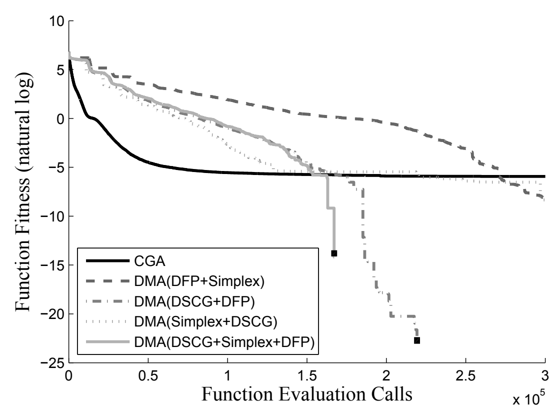


Figure 5: Search performance of CGA and DMAs on 30D Griewank

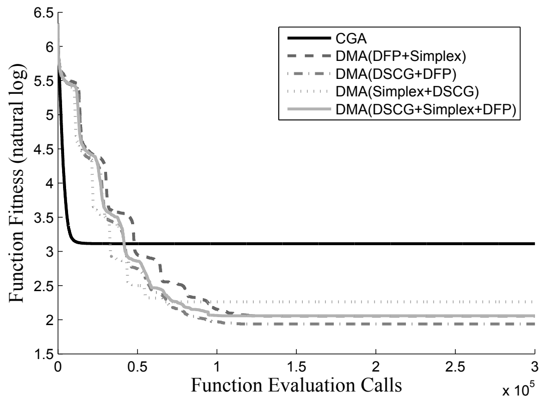


Figure 6: Search performance of CGA and DMAs on 30D Rastrigin

for DMAs with (DSCG + Simplex) or (DFP + Simplex) are similar to that of CMAs using DSCG or DFP, respectively, on both the benchmark problems. On the other hand, it is interesting to observe that DMA (DSCG + DFP) and DMA (DSCG + Simplex + DFP) fare better than both CMA(DSCG) and CMA(DFP) on the Griewank function. Note that in DMA, an individual may be infected with different memes throughout the entire search. This has the benefits of giving each individual the opportunity to be refined by different individual learning procedures, hence the possibility of better results.

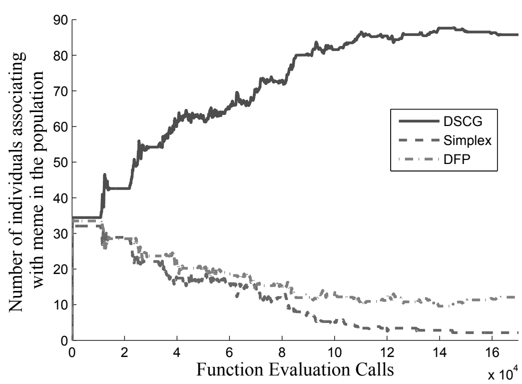


Figure 7: Meme distribution during the search process of DMA (DSCG + Simplex + DFP) on 30D Griewank

More details on the diffusion process of DMA (DSCG + Simplex + DFP) on the benchmark functions are depicted in Figures 7 and 8. On Griewank function, DSCG meme outperforms the other two memes (refer to Figure 3), therefore the number of individuals infected with the DSCG meme at the final stage of the search is much higher (see Figure 7). In this case, most of the runs ended up with the DSCG meme spreading over the entire population. On the other hand, the DSCG and DFP memes fare equally well on the Rastrigin function (refer to Figure 4), thus both memes possess relatively equal number of infected individuals at the end of the search process. Overall, the Simplex meme is deem to be incapable of bringing about benefits to the search on both the Griewank and Rastrigin functions.

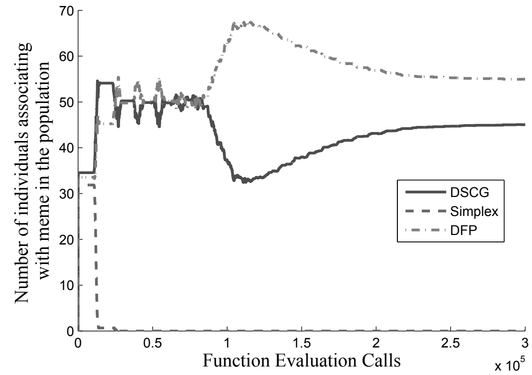


Figure 8: Meme distribution during the search process of DMA (DSCG + Simplex + DFP) on 30D Rastrigin

4.4 The neighborhood size in cellular structure

One of the core parameters of both CGA or DMA is the neighborhood size used in the diffusion process. Here, the neighbors of an individual or a cell is defined by the threshold used, in the form of (i.e. $|dx| + |dy|$). Figure 9 illustrates the neighbor set of one individual with the distance threshold set to 1 and 2. Following the convention of Cellular GA, the neighborhood structure is circularly wrapped, i.e., individuals in the last row of the grid are neighbors with distance 1 from the individuals in the first row of the grid. Such a rule help enforce all individuals in the population to have equal number of neighbors.

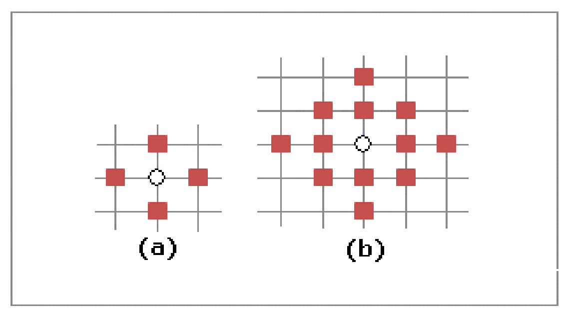


Figure 9: Neighborhood structure in meme selection algorithm (a) Distance = 1 (b) Distance = 1 and 2

Here, we study the effect of neighborhood sizes for distance thresholds $d = 1$, 2 and 3 on DMA (DSCG + DFP). Table 2

Table 2: Search performance of DMA on 30D Griewank

	100,000 evaluations			300,000 evaluations		
	d=1	d=2	d=3	d=1	d=2	d=3
Best	0	0	0	0	0	0
Worst	1.3262	1.7741	2.2600	0	0	0
Mean	0.3777	0.5292	0.4332	0	0	0
Std.	0.4423	0.4518	0.5476	0	0	0
Success	12%	8%	10%	100%	100%	100%

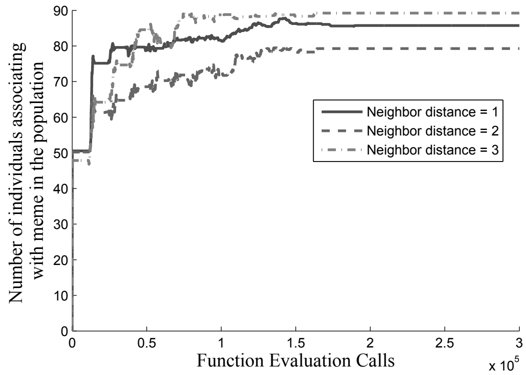


Figure 10: Meme distribution of DSCG during the search process of DMA (DSCG + DFP) on 30D Griewank

presents the statistical results of DMA (DSCG + DFP) searching on the Griewank function, i.e., for best and worst runs together with mean and standard deviation at 100,000 and 300,000 evaluations are reported.

Figure 10 depicts the distribution of individuals that is infected with DSCG meme along the DMA (DSCG + DFP) search for different neighborhood sizes. Since the neighbors of an individual increases with Manhattan distance threshold used, DMA of larger neighborhood sizes would generally diffuse the memes more rapidly. For example, an individual may infect up to a maximum of 24 neighbors when a distance threshold d of 3 is considered, while influences only 12 and 4 neighbors for distance threshold of 1 and 2, respectively.

5. CONCLUSIONS

In nature, it is widely accepted that individuals are products of the interaction between genetic evolution and cultural evolution. In the context of optimization, the 2^{nd} and 3^{rd} generations of Memetic Algorithm mimic the process of cultural transmission and evolution with the purpose of increasing the chance of employing appropriate memes, while at the same time, yielding robust and improved search performance.

In this paper we have studied an instance on non-genetic transfer of meme in the context of evolutionary optimization. A 2^{nd} generation Memetic Algorithm with meme diffusion (DMA) is also proposed and investigated. Using the natural overlapping neighborhoods of cellular structure, memes are allowed to diffuse or spread across the population. Empirical study on DMA using two commonly used test functions shows that non-genetic transmission of memes via diffusion not only helps promote spread of memes appropriate for the problem of interest, but also facilitates collaboration between diverse memes, thus bringing about benefits in terms of improved search performance which would not be possibly achieved when only single meme are considered.

6. REFERENCES

[1] E. Alba and M. Tomassini. Parallelism and evolutionary algorithms. *IEEE Transactions on Evolutionary Computation*, 6(5):443–462, 2002.

[2] E. Burke, P. Cowling, P. De Causmaecker, and G. Berghe. A Memetic Approach to the Nurse Rostering Problem. *Applied Intelligence*, 15(3):199–214, 2001.

[3] L. Cavalli-Sforza. Cultural Evolution. *Integrative and Comparative Biology*, 26(3):845–856, 2003.

[4] W. Davidon. Variable Metric Method for Minimization. *SIAM Journal on Optimization*, 1:1, 1991.

[5] R. Dawkins et al. *The Selfish Gene*. Oxford University Press, 1989.

[6] A. Hughes. *Evolution and Human Kinship*. Oxford University Press US, 1988.

[7] H. Ishibuchi, T. Yoshida, and T. Murata. Balance between genetic search and local search in memetic algorithms for multiobjective permutation flowshop scheduling. *IEEE Transactions on Evolutionary Computation*, 7(2):204–223, 2003.

[8] G. Kendall, E. Soubeiga, and P. Cowling. Choice function and random hyperheuristics. *4th Asia-Pacific Conference on Simulated Evolution And Learning, SEAL 2002*, pages 667–671.

[9] N. Krasnogor. Coevolution of genes and memes in memetic algorithms. *Graduate Student Workshop*, page 371, 1999.

[10] N. Krasnogor and S. Gustafson. Toward truly "memetic" memetic algorithms: discussion and proof of concepts. *Advances in Nature-Inspired Computation: The PPSN VII Workshops. PEDAL (Parallel, Emergent and Distributed Architectures Lab). University of Reading*, 2002.

[11] M. H. Lim and Y. L. Xu. Application of hybrid genetic algorithm in supply chain management. *Special issue on ŞMulti-Objective Evolution: Theory and ApplicationsŤ, International Journal of Computers, Systems, and Signals*, 6(1), 2005.

[12] P. Moscato. On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms. *Caltech Concurrent Computation Program, C3P Report*, 826, 1989.

[13] J. A. Nelder and R. Mead. A simplex method for function minimization. *Computer Journal*, 7(4):308–313, 1965.

[14] Y. S. Ong and A. J. Keane. Meta-Lamarckian learning in memetic algorithms. *IEEE Transactions on Evolutionary Computation*, 8(2):99–110, 2004.

[15] Y. S. Ong, M. H. Lim, N. Zhu, and K. W. Wong. Classification of Adaptive Memetic Algorithms: A Comparative Study. *IEEE Transactions on Systems, Man and Cybernetics – Part B.*, 36(1):141, 2006.

[16] H. P. Schwefel. *Evolution and optimum seeking*. Wiley New York, 1995.

[17] J. E. Smith. Co-evolving Memetic Algorithms: Initial Investigations. *Parallel Problem Solving from Nature VII (PPSN)*, pages 537–546, 2002.

[18] J. Tang, M. H. Lim, and Y. S. Ong. Diversity-Adaptive Parallel Memetic Algorithm for Solving Large Scale Combinatorial Optimization Problems. *Soft Computing Journal*, 11(9):873–888, July 2007.