An Evolutionary Algorithm Derived from Charles Sanders Peirce's Theory of Universal Evolution

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ABSTRACT

Historically, Evolutionary Algorithms (EAs) have been important for Evolutionary Computation (EC) community for two reasons: 1) As a simulation of evolutionary processes as they happen in nature, and 2) as a solution to hard optimization problems. With the passage of time EAs have become increasingly focused on function optimization. Given this narrowing of vision in the EC community, it is worth revisiting a paper written in 1997 by Hans-Paul Schwefel on the future challenges for EC. In that paper the author argues that the more an algorithm models natural evolution at work in the universe, the better it will perform (even in terms of function optimization). The present paper tests Schwefel's hypothesis by designing an EA based on Charles Peirce's theory of evolution. Peirce's theory not only accounts for biological evolution on earth (as other theories of evolution do) but also offers an account of global, cosmological and universal evolution. In going beyond just biological evolution, Peirce's theory of evolution meets the criteria suggested by Schewefel in his 1997 paper. The present paper mainly contributes in testing the Peircean EA on an extended set of benchmark optimization functions and compares the results with a classical EA that is based on Darwin's theory of evolution. In majority of these comparisons the performance of the Peircean EA is notably superior. This exercise provides preliminary results that support Schwefel's hypothesis. In return the experiments in evolutionary computation help provide important insights into Peirce's theory of evolution.

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1. INTRODUCTION

John Holland's motivation behind his pioneering Genetic Algorithms (GA) model was to simulate biological adaptive systems. In other words, Holland sought to model biological evolution as proposed in Darwin's theory. After Holland his students became increasingly focused on designing GA for solving optimization problems [5]. While the practical need for optimization in GA is indeed important, it was only a marginal concern in Holland's original GA. Because his GA sought to model evolution in the natural world, Holland had to keep in view the fact that for complex adaptive systems "improvement is usually much more important than optimization" [6]. This is an important point to keep in mind because as De Jong notes: "There is a subtle but important difference between 'GAs *as* function optimizers' and 'GAs *are* function optimizers' " [4]. De Jong goes on to point out that there are important insights to be had when this difference is understood and its implications are taken into account in developing GAs (and we may add all evolutionary algorithms here).

This sentiment has been echoed, in slightly different words, by two other pioneers in Evolutionary Algorithms (EAs). Hans-Paul Schwefel, one of the founders of Evolution Strategies notes that "organic evolution certainly does not only aim at finding static optima just once and with ultimate precision. Organic evolution happens within an ever-changing environment, where evolvability is more important than precision" [11]. Lawrence J. Fogel, pioneer in Evolutionary Programming notes in [2] that even though,

> [t]he solution of complex engineering problems is important, but the use of evolutionary algorithms need not be restricted to mere function optimization. The methods can also be used to gain an understanding of how competitive or co-

operative agents may interact given a variety of different available resources and purposes.

The last sentence again stresses upon the significance of understanding the natural phenomena, and that one of the objectives of EC is to help natural sciences in this regard. David B. Fogel aptly notes that "efforts in evolutionary computation commonly derive from one of four different motivations: improving optimization, robust adaptation, machine intelligence, and facilitating a greater understanding of biology" [2]. On the one hand, this clearly indicates that the spirit of EC is multi-faceted and cannot be reduced in its entirety to function optimization, or any of the other three motivations for that matter. But at the same time it can lend itself to the view that there is an either-or situation for the EC community–either one can be in EC to improve function optimization or else, to understand the processes of natural evolution better. The two tasks appear to be independent of each other apparently and do not seem to be meaningfully related.

Perhaps it is because of this sectional view of EC that over the years the practical focus in EC is increasingly being "reduced" to factors such as efficiency, engineering applications and standardizations. A careless reading of the foregoing could be taken as a suggestion that the importance of function optimization or its efficiency in EAs is being trivialized. We are arguing something very different. What is being suggested is that function optimization and its efficiency can be enhanced by recognizing that there is a direct relation between understanding the natural processes of evolution in greater detail and this could help the EC community in improving the workings of their respective evolutionary algorithms.

Our call for revisiting Schwefel and other pioneer's research agenda is not because we are interested in the fulfillment of the initial promises, in and of themselves, or that we are not inclined towards looking at EAs as function optimizers. On the contrary, we bring to attention those unfulfilled promises only so far as they can help improve the function optimization capabilities of EAs. The reason we chose Schwefel to make a case is because of the clarity with which he has laid bare the relation between two things that are widely viewed otherwise as being largely unrelated. He says that,

> Current evolutionary algorithms are certainly better models of organic evolution. Nevertheless, they are still far from being isomorphic mappings of what happens in nature. *In order to perform better*, an appropriate model of evolution would have to comprise the full temporal and spatial development on the earth (a real global model) if not within the whole universe. We must be more modest in order to understand at least a little of what really happens – as always within natural sciences.

We will refer to this passage as **Schwefel's hypothesis**. Schwefel's hypothesis seems to ask for a model of evolution that goes beyond biological evolution as well and encompasses global, cosmological and universal evolution.

We feel that while it is important to advance EC as a legitimate engineering discipline[1], it is equally important to bring EC into a dialogue with other domains of evolutionary sciences, especially evolutionary philosophy and biology. Towards this end we introduce the evolutionary theory of Charles Sanders Peirce–the evolutionary philosopher, mathematician, semiotician, and scientist par excellence [10]. Typically evolution has been confined to biological processes, which help only explain the last few billion years of development within the universe. Being a throughgoing evolutionary philosopher Peirce sought to understand not only biological life, but also the emergence of all inanimate and animate matter as well as the laws of nature shaping their behavior, in evolutionary terms.

This paper aims to, first of all, build a partnership between Schwefel and Peirce (and in turn between evolutionary computation and evolutionary philosophy respectively). More importantly, its aim is to test this partnership across disciplines, experimentally. The metric for the test is provided by Schwefel's hypothesis, i.e. by basing our EA model on a universal evolutionary theory of Peirce, if the performance improves in function optimization sense, then we will have some preliminary evidence of the relevance of Schewefel's insight for the EC community. Next section discusses the Peircean evolutionary framework briefly. A novel evolutionary algorithm is extracted from the Peircean framework at the end of Section 2. It is then tested on mathematical benchmark problems and the results and experiments explained in Section 3. Based on the comparative results from our experimentation, we claim that EC community stands to gain from the validation of Schwefel's hypothesis. On the flip side, Peirce's theory also stands to gain important insights from the EA experiments, as some of his hypotheses also get verified consequently, bringing it full circle.

2. CHARLES SANDERS PEIRCE'S THEORY OF EVOLUTION

According to Jacques Monod, Darwin's theoretical explanation for evolution is an exquisite mix of "chance and necessity" [9]. In non-philosophical terms it is a combination of a variety of chances and a variety of laws. In order for Darwinian evolution to work it takes as a given, not only these two agents, but ironically the first batch of replicating life as well. Being a naturalist, Darwin did not make an attempt to try and relate the two apparently warring agents (chance & necessity), or how they "evolved" themselves before playing a role in the evolution of the universe and its living forms. However, there is one man that did that after Darwin.

Charles Sanders Peirce, the 20th century evolutionary pragmatist, has made major contributions to numerous fields such as logic and philosophy of science, formal and mathematical logic, topology, linguistics, epistemology and semiotics. For Peirce, biological evolution along with its mechanisms did not suddenly come into existence in the universe some four billion years ago with the emergence of the first forms of self-replicating RNA. It is a process that is at least fourteen billion years old – or as old as the universe itself. Biological evolution is only a specific manifestation of a more

[1]Task Force (TF) on Future Directions in Evolutionary Computation (FDEC) had been part of the Evolutionary Computation Technical Committee (ECTC), IEEE Computational Intelligence Society (CIS). The TF held an annual Workshop as part of the IEEE Congress on Evolutionary Computation.

general phenomenon: evolution at the cosmological level. A natural problem arises regarding the terms that should be used to describe the basic elements for such a universal evolutionary theory. If biological terms are used, they are instantly rendered useless at the level of physics and chemistry and cosmology, and vice-versa. Hence, Peirce uses the technical terms "Firstness," "Secondness," and "Thirdness" (which he calls "categories") to describe chance, necessity, and habit respectively[2].

In the case of biology Peirce extends the almost linear two step evolutionary process of random variation followed by natural selection into a non-linear triadic process. He says, First is the principle of individual variation or sporting; Second, the principle of heredity transmission; and Third, the process whereby the accidental characteristics become fixed (including, but not limited to the elimination of unfavorable characters by natural selection.) [10, 6.32]

For Peirce, wherever there is evolutionary growth in the universe, there is dynamic interaction between chance, necessity, and habit. Evolutionary growth, in the most general sense, is a movement from pure chance or possibility (Firstness) to brute facts of necessity (Secondness) by the gradual spreading of habit (Thirdness). The following quote summarizes Peirce's theory of evolution at the cosmological level:

> This theory is that the evolution of the world is hyperbolic, that is, proceeds from one state of things in the infinite past, to a different state of things in the infinite future. The state of things in the infinite past is chaos, tohu bohu, the nothingness of which consists in the total absence of regularity. The state of things in the infinite future is death, the nothingness of which consists in the complete triumph of law and absence of all spontaneity. Between these, we have on our side a state of things in which there is some absolute spontaneity counter to all law, and some degree of conformity to law, which is constantly on the increase owing to the growth of habit. The tendency to form habits or tendency to generalize is something which grows by its own action, by the habit of taking habits itself growing. Its first germs arose from pure chance. [10, 8.137]

Does the foregoing discussion have any implications for the EC community? In other words, when the underlying theory of evolution *evolves* from a serial two-ness to a dynamic three-ness, how does that affect the EC models consequently? For detailed philosophical and technical discussion on Peirce's theory and the long process of extracting an algorithm out of it, refer to [1]. Taking the lead from there, one of the goals of this paper is to test Schwefel-Peirce hypothesis for EC on an extended set of benchmark functions. For the want of space, we will only briefly describe the algorithm and then get to the results.

[2]Peirce's use of habits is different from its Lamarckian usage: "For Peirce, habits are not provisional adaptive responses to fluctuating environmental conditions; they are steps on the universal road from indeterminacy to law, a road traveled by objects as well as by organisms...Habit-taking is a plastic faculty. The peculiar characteristic of habit is: "not acting with exactitude" " [8, pg. 365]

2.1 Peircean Evolutionary Algorithms

In most basic terms the standard EAs implementation is a two-pronged strategy that comes up in EA literature under different names: exploration-exploitation, variation-selection, chance-necessity [3]. If we could re-write that in Peircean terminology it would roughly translate into Firstness Secondness respectively. The foremost difference is that the Peircean EA would have a Third (generalizing) element working simultaneously, that we implement in the form of clustering. The second difference is that for Peirce the meaning of Firstness is not confined to variation, and the meaning of Secondness is not captured entirely by selection either. But thirdly and more importantly the relationship and interplay between the three elements of evolution builds an entirely different system and hence gets translated into an entirely different evolutionary algorithm.

```
population = generate random initial population //Firstness
while stopping criteria not met do
    parameter tuning //Thirdness
    cluster analysis(population) //Thirdness
    for each cluster i
        cluster_fittest_i = intra-cluster evolution (cluster_i) //Secondness
    end for
    population_fittest = inter-cluster evolution(cluster_fittest_1..i) //Secondness
    add i random individuals to the population //Firstness
```

Figure 1: Pseudo code for Peircean Evolutionary Algorithm

Figure 1 lays out the basic algorithm in the form of a pseudo code. The Thirdness principle's most important contribution is that the population shall cooperate and survive in cluster based communities. The Secondness principle dictates the terms under which individuals and clusters interact with each other through various operators of recombination and selection. The Firstness principle introduces and retains novelty in the population through various operators of variation.

Peircean EA, when stated simply, is this: Until the stopping criteria are met, 1) distribute the population in clusters. 2) First each cluster internally generates its next generation. 3) Next each cluster's fittest individuals make an inter-cluster information exchange. 4) Finally a small number of new individuals also get introduced into the population. For detailed discussion of the Peircean as well as the Darwinian EA, parameter settings and the experimental setup, refer to [1].

3. EXPERIMENTAL RESULTS

For this article the extended benchmark of 15 mathematical functions of up to 100 dimensions has been used[3]. For the lack of space refer to [7] for detailed description of each function. For most of the functions the 30 dimensional form has been used, while F7 and F9 are 100-D. Table 1 lists the comparative results of both the Peircean (P-EA) and the classical Darwinian evolutionary algorithm (D-EA) when they are run for 50 times against each function. For 50 independent

[3]Results for 3 out of 15 functions were pending till the time of submission for this article.

Table 1: Comparison between Peircean-EA and Darwinian-EA

F.	Mean number of generations		Mean function value (standard deviation)		Global min func. value
	P-EA	D-EA	P-EA	D-EA	
F1	2895.2	2286.48	-12569.3 (0.6195)	-10962.6 (305.88)	-12569.4
F2	2308.22	3955.72	0.0069 (0.0017)	26.61 (4.08)	0
F3	1502.82	1513.74	0.2730 (0.0324)	2.3272 (0.2686)	0
F4	1618.92	1689.12	0.0198 (0.0233)	0.4264 (0.4000)	0
F7	8984.52	2656.7	-95.08 (0.8304)	-73.93 (1.8858)	-99.2784
F9	8414.04	3826.02	-78.32 (0.0087)	-58.68 (1.5735)	-78.3324
F10	7840.6	1764.06	52.71 (30.02)	1899.87 (900.19)	0
F11	1502.74	1527.76	0.0570 (0.0097)	0.0780 (0.1436)	0
F12	1620.76	1606.7	0.5241 (0.2964)	0.5969 (0.3046)	0
F13	1500	1647.4	0.0146 (0.0023)	0.0274 (0.1416)	0
F14	10000	2770.18	3307.14 (2946.47)	325689.5 (92779.9)	0
F15	2750.94	3120.78	0.4978 (0.5710)	29.1570 (13.3290)	0

runs, what the table lists against each function is how P-EA and D-EA perform statistically in terms of, 1) the average number of generations it took the EA to converge, 2) the average of the best function values that the EA converged at, and 3) the standard deviation of those values.

The most interesting observation is that apart from one exception (F14), P-EA, by the time it stops, is almost always very close to the global minimum value for each function, that too with a small standard deviation value. This is not the case for D-EA. But more important than that is the fact that for P-EA evolvability, improvement and growth seem to be vital. In terms of number of generations (or function evaluations equivalently) P-EA seems to be more efficient or at par with D-EA in most of the cases. In some cases where D-EA makes an early stop (e.g. F7,F9,F10,F14) it is always the case where D-EA has stopped because of premature convergence to a local minimum due to stagnation of its population. This fact is evident by looking at the respective mean function value columns. In all of these tough specific cases, P-EA keeps on evolving its population and gets much closer to the global minimum before stagnating. The results would make more sense when the above-mentioned analysis is coupled with the stagnation analysis and cluster analysis [1].

4. CONCLUSIONS

This short paper explores the idea of opening up the initial unfulfilled promises of the EC pioneers. It does that by bringing Peirce's universal theory of evolution into a conversation with Schwefel's hypothesis. It then tests this new partnership on an extended benchmark of mathematical functions. The analyses of this extended benchmark results are preliminary at this stage but they do 1) help affirm Peirce's theory of evolution to some extent, 2) bridge the natural theory-function optimization gap, 3) potentially present a natural solution to the issue of premature convergence/stagnation but most importantly, 4) invite the EC community to revisit the historically legitimate but forsaken possibilities for its future exploration.

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