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Anna Sarosiek
Uniwersytet im Komisji Edukacji Narodowej w Krakowie
Poland
e-mail: anna.sarosiek@up.krakow.pl
ORCID: 0000-0002-7799-6278

Roman Krzanowski
Uniwersytet Papieski Jana Pawła II w Krakowie
Poland
e-mail: roman.krzanowski@upjp2.edu.pl
ORCID: 0000-0002-8753-0957

INTEGRATION OF BIOSEMIOTICS AND GENETIC ALGORITHMS

Abstract. This paper explores the integration of genetic algorithms (GAs) with biosemiotic concepts. It presents an overview of GAs and outlines their limitations. Then, it introduces biosemiotic principles and discusses their integration with GAs. The paper concludes that incorporating biosemiotic paradigms into GAs can significantly improve their performance and applicability, bridging the gap between computational models (specifically GA) and the complex nature of genetic processes.

Keywords: genetic algorithms, biosemiotics, AI, computational biology, context-aware models, natural systems, metaheuristics.

Introduction

The limitations of computational models of biological processes, like in genetic algorithms (GAs), prompts a reconsideration of the relationship between biological processes and their computational models. The question is whether these algorithms truly represent the complex processes of nature or if they are merely simplified tools.. If the world is seen as one grand computer, as in pancomputaionalism[1], it would blur the lines between biology and computer science. Biosemiotics, (as defined e.g., by Favareau [2010]), introduces the concept of meaning and communication in biological systems, exploring the interpretive nature of interactions among organisms. This perspective hold the promise of a richer way to model natural processes. The

paper explores the connection between GA and biosemiotics arguing that adding biosemiotic concepts to GA will improve GA performance in resolving complex optimization problems.

The paper begins with a brief overview of GAs, their mechanisms, focusing on their limitations, highlighting the similarities and differences between GAs and genetic processes. It then discusses the principles of biosemiotics and their applicability to GA. The paper further examines the philosophical and practical challenges of combining GAs with biosemiotics, particularly in modeling biological systems. Finally, it discusses the benefits of adopting a biosemiotic perspective in GAs, the perspective that could lead to more adaptable and efficient artificial systems. The paper also highlights that biosemiotic processes occur at various scales of life, from unicellular microorganisms to complex multicellular organisms, demonstrating the universal applicability of these concepts.

GAs – Key Concepts

GAs are algorithms for solving complex, poorly defined problems by imitating certain molecular mechanisms underlying evolution by means of natural selection. GAs have been extensively discussed in the literature, including works by John H. Holland (1975), David E. Goldberg (1989), and Kalyanmoy Deb (1995; 2000), among many others.

GAs are algorithmic metaheuristics – methods for finding suboptimal solutions in complex, poorly defined problem spaces, drawing inspiration from nature and evolutionary processes (Goldberg, 1989; Holland, 1975; Eiben & Smith, 2003). They are a subset of evolutionary algorithms, a class of algorithms inspired by various aspects of evolution in the natural world (Mitchell, 1998). In problems where GAs are applied, the optimal solution is not known in advance (in the sense of an analytical solution, i.e., we do not have a clearly defined maximum, minimum, or objective function). The solution is found through iterative application of selection, mutation, and recombination operators, which are perceived as being somewhat similar to DNA processing mechanisms in natural systems.

GAs have found many applications in optimization problems. For instance, in logistics, they optimize delivery truck routes to minimize travel time and fuel consumption. In pharmaceuticals, they help design new drugs by predicting the best molecular structures for targeting specific diseases. In automation, GAs streamline production, enhancing efficiency

and reducing waste. Many more applications of GAs have been developed (see e.g., Firas et al., 2018; Burkhart and Gabriel, 2023; Thompson, 2023).

GAs mimic some aspects of natural evolution through operations (or transformations) of selection, crossover, and mutation. The GA algorithm starts by initializing a population of potential solutions represented by binary strings (denoted as chromosomes). This population is created randomly to ensure diversity and avoid premature convergence (Holland, 1975; Thompson, 2023). At each iteration, through the sequential application of these operators, possible solutions to the problem are generated. Each solution is then evaluated using a fitness function (optimization metric) to measure its quality (Goldberg, 1989). In the next iteration, only the subset of solutions with the best fitness scores is retained. This subset is processed in the same sequence of transformations. The algorithm ends when no further improvements in fitness can be found (Holland, 1975; Goldberg, 1989; Deb, 1995; 2000).

Selection methods, such as roulette wheel or tournament selection, favor solutions with higher fitness for the next generation (Holland, 1975; Deb, 2000). Crossover combines traits from parent chromosomes to create new offspring, introducing novelty and enabling exploration of new solution spaces (Deb, 1995). Mutation introduces random changes to chromosomes, preventing stagnation and ensuring genetic diversity (Goldberg, 1989).

However, GAs in their traditional form do not account for certain evolutionary processes observed in ature, such as gene migration and genetic drift. Gene migration and genetic drift exemplify the semiotic nature of genetic processes, where information exchange and random variability reflect complex biological signaling. These processes, though not part of the standard GA framework, are introduced here to explore areas where biosemiotics can significantly broaden the rather narrow view of evolutionary mechanisms provided by genetic algorithms. Gene migration, for instance, allows the transfer of genetic material between populations, enhancing genetic diversity. Genetic drift, on the other hand, involves random fluctuations in allele frequencies, which can significantly impact smaller populations regardless of fitness. Incorporating these processes into GAs could enrich their modeling capabilities, providing a more nuanced reflection of natural evolutionary dynamics (Kimura, 1983; Slatkin, 1987).

Many more variants of genetic operators and subsequent operations have been proposed. However, they do not fundamentally alter the essence of genetic algorithms as described here (Thompson, 2023).

Biosemiotics

Biosemiotics emphasises the importance of interspecies interactions. In nature, organisms do not exist in isolation; they are part of complex networks involving symbiosis, predation, competition, and other relationships (Schumer et al., 2014). These interactions are biological and semiotic, meaning that organisms exchange signs and signals that influence their behaviour, survival, and reproduction; the signals exchange between organisms have meaning to them. These semiotic interactions manifest across all levels of biological organization, from unicellular organisms that rely on chemical signaling to multicellular organisms employing complex sensory and communication systems.

Cooperation extends beyond multicellular organisms, as illustrated by Lynn Margulis's groundbreaking theory of endosymbiosis (Sagan 1967). This theory demonstrates how symbiotic relationships between microorganisms led to the evolution of complex eukaryotic cells. Incorporating this microbial perspective into GAs could inspire novel approaches to modeling cooperation, where individual solutions work symbiotically to achieve global optimization.

Biosemiotics introduces the concept of Umwelt – the unique way each organism perceives its world. Umwelt refers to the environment experienced by an organism, which receives, processes, and reacts to stimuli in its own specific way (von Uexküll, 1934). In biosemiotic perspective every organism lives in its own unique universe, interpreting environmental signals through its senses and needs. In the context of GAs, modeling Umwelt allows for the simulation of individualized solution perspectives

Biosemiotics emphasises that organisms create, interpret, and respond to signs in their environment. Beyond mutations, biosemiotics reveals the importance of alternative mechanisms of genetic change, such as horizontal gene transfer (HGT), particularly in microorganisms. HGT facilitates the exchange of genetic material between cells, enabling rapid adaptations and significant genomic restructuring. Moreover, HGT accelerates evolutionary processes, especially in dynamic environments, by rapidly integrating beneficial traits that enhance survival and adaptability. This process exemplifies the semiotic dimension of genetic exchange, as it often relies on environmental cues to initiate and regulate the transfer (Jalasvuori 2012, Dimitriu et al. 2014). Such mechanisms emphasize that evolutionary processes are not solely determined by random mutations but are shaped by dynamic interactions within ecosystems.

Further, biosemiotics shows that evolutionary processes are shaped by perception, cognition, and communication (Sharov, Maran, Tønnes-

sen, 2016). By incorporating these biosemiotic processes, genetic algorithms can not only better reflect the complexity of natural systems but also pave the way for groundbreaking advances in adaptive and context-aware computational models.

GA – A Biosemiotic Perspective

GAs, view organisms and their environments as static and uniform, which limits the understanding of dynamic interactions. By integrating GAs with biosemiotic concepts, we can model these processes more realistically, considering how organisms subjectively perceive and react to stimuli, such as bacterial chemotaxis or quorum sensing. This integration is particularly valuable for problems with complex, poorly defined solution spaces and poorly specified objective criteria. This will enable technological progress and allow for a better understanding and imitation of the complexity of natural systems. A biosemiotic perspective also allows for more dynamic and diverse modeling of interactions between organisms and their environments.

Gas models usually focus on single populations or simple relationships, overlooking the richness of biological interactions. To better reflect natural evolutionary processes, these algorithms should incorporate complex communication networks between organisms. Interspecies interactions also affect the transition from genotype to phenotype. This transition in biology is a complex network of interactions and sign processes. One gene can influence many traits, and one trait can result from the actions of many genes, all within a semiotic context. Incorporating semiotic interactions into the genotype-to-phenotype mapping in GAs could enable greater diversity and adaptability of solutions by reflecting the complexity of natural systems.

In biological systems, genes not only encode information but are part of a complex network of signs and signals that organisms interpret and respond to (Hoffmeyer, 2008; Barbieri, 2001). This semiotic dimension is largely absent in GAs, which treat genetic information in a more mechanical and less interpretive manner. The reduction of biological processes to mere data processing strips away the layers of meaning and context that are crucial for understanding living systems.

Interspecies interactions, such as symbiosis, predation, and competition, play a crucial role in these processes, affecting which phenotypic traits develop. In the context of GAs, the transition from genotype to phenotype is crucial because it helps understand how coded solutions (genotypes) translate into actual problem solutions (phenotypes). GAs simplify these in-

teractions, focusing on optimization rather than the interpretive processes seen in natural evolution. These limitations are addressed from a biosemiotic perspective, focusing on key processes such as selection, recombination, mutation, gene migration, and genetic drift.

Selection

Natural selection, seen through the lens of biosemiotics, involves not just survival and reproduction but also the continuous exchange of semiotic signals within and between organisms and their environment. This semiotic exchange occurs through various communication channels such as chemical signals (e.g., pheromones), sounds, visual signs, and touch. Each of these channels allows organisms to convey information that can influence their behaviour, metabolic processes, and decisions related to survival and reproduction (Kull, 2005).

In contrast to multicellular organisms with advanced sensory systems, microorganisms rely on simpler, yet highly effective, signaling mechanisms. For instance, bacterial chemotaxis – a process where bacteria move toward or away from chemical gradients – can be viewed as an elementary semantic phenomenon (Kłóś, Płonka 2021). Modeling such processes in GAs could extend their application to systems where decision-making relies on basic yet robust signal interpretation. In this way, the semiotic exchange of signals is an integral part of the natural selection process, influencing which organisms are better able to adapt to changing environmental conditions.

In GAs, selection is purposeful and based on defined criteria, unlike natural selection, which arises from complex interactions between organisms and their environment (Gildenhuys, 2024).

Recombination

Genetic recombination during meiosis increases genetic diversity by exchanging DNA segments between chromosomes, creating new combinations of alleles. This process influences evolutionary adaptations and biodiversity. However, in GAs, the crossover process, which mimics some aspects of genetic recombination, lacks the semiotic richness of biological systems. In natural systems, each exchange of genetic material is a sign process influenced by various internal factors, such as the cell's state and metabolism, and external factors, such as environmental signals.

For example, in response to environmental stress, organisms can activate specific signaling pathways that affect the recombination process, thereby promoting adaptations that increase survival chances (Hoffmeyer, 2008).

GAs typically treat the crossover process in a simplified manner, as a straightforward exchange of genes without considering the complex semiotic interactions. As a result, these algorithms do not reflect the richness and dynamics of genetic processes occurring in nature.

Mutation

Mutations in nature introduce genetic variability, which is essential for evolution. They can result from DNA replication errors or external factors such as UV radiation, chemicals, or viruses. From a biosemiotic perspective, mutations are not random but are influenced by the semiotic environment of the organism. Biosemiotics suggests that organisms are not merely passive recipients of mutations but actively interpret and respond to signals from their surroundings, which can affect the frequency and nature of mutations. In response to environmental stress, organisms can activate specific defence mechanisms that not only protect them from damage but also increase the frequency of mutations in specific regions of the genome, potentially promoting adaptations. For example, in response to UV radiation, skin cells can activate repair mechanisms that simultaneously increase mutation rates, potentially leading to the emergence of new adaptive traits (Hoffmeyer, 2008; Barbieri, 2001). These mechanisms are regulated by signalling networks that encompass molecular and cellular communication processes, reflecting the complexity of semiotic information exchange.

At the unicellular level, microorganisms demonstrate adaptive responses to environmental stress through mechanisms such as the production of heat shock proteins (HSPs). These proteins stabilize and refold damaged proteins, enabling cells to survive under adverse conditions (Lund 2001, Mayer 2021). This highlights how even simple organisms actively respond to environmental signals, emphasizing the semiotic nature of these interactions.

In GAs, mutations are controlled and introduced to add variability and avoid local minima in the search space (Fogel, 2006). However, this approach reveals a lack of interpretative complexity seen in natural systems, where environmental signals such as resource availability, the presence of pathogens, or climatic changes can influence cellular choices regarding DNA replication and repair.

Gene migration

Gene migration, also known as gene flow, involves the movement of individuals or their genetic material between different populations, thereby introducing new genes and increasing genetic diversity. In microorganisms, gene migration often takes the form of plasmid transfer or HGT, allowing for the rapid spread of advantageous traits such as antibiotic resistance. These exchanges exemplify the semiotic nature of genetic migration, as they involve interpreting environmental signals to determine when and where to transfer genetic material (Jalasvuori 2012).

This process is crucial for maintaining genetic variability within populations and can occur through various mechanisms such as migration, dispersal, and the exchange of genetic material during reproduction (Slatkin, 1987). From a biosemiotic perspective, this is not merely a simple exchange of genetic material, but complex semiotic exchanges that are crucial for the adaptability and resilience of organisms. Every movement of organisms and the introduction of new genes into a population involves an exchange of information. This means that organisms not only transfer their genes but also communicate with the new environment and other organisms through various signals and signs, which can include chemical signals, pheromones, sounds, behavioural patterns, and other forms of communication. These actions enable organisms to better adapt to new environmental conditions and to interact with other individuals in the new population (Kull, 2005). Such semiotic exchange can increase the adaptability of organisms because it allows them to better respond to changing environmental conditions and the presence of new competitors, predators, or resources. Moreover, through continuous exchange of information, organisms can enhance their resistance to environmental stressors and pathogens, which is crucial for their survival and reproductive success. This ongoing gene flow helps maintain genetic diversity, allowing populations to adapt to changing environmental conditions and improving their overall fitness and resilience (Slatkin, 1987).

Genetic Drift

Genetic drift is another important evolutionary mechanism that acts like an evolutionary lottery, involving random changes in allele frequencies within a population. Alleles are different versions of a gene that can exist at a specific locus on a chromosome. Genetic drift occurs when these al-

lele frequencies fluctuate randomly over time, leading to significant genetic changes, especially in small populations. This process happens independently of natural selection and can result in the loss or fixation of alleles purely by chance (Kimura, 1983). From a biosemiotic perspective, genetic drift can also be seen as a semiotic process, though more subtle than gene migration. Genetic drift involves certain alleles becoming more common or rarer in a population not because of natural selection, but due to random fluctuations. In small populations, genetic drift can quickly lead to significant changes in the genetic composition of the population, regardless of whether these changes are beneficial, neutral, or harmful (Kimura, 1983). From a biosemiotic perspective, genetic drift can be interpreted as random changes in the "language" of a population's genetics. Unlike more directed and purposeful semiotic processes, such as natural selection or gene migration, genetic drift represents random changes in the semiotic communication of organisms at the genetic level. Although these changes are random, they can affect how the population as a whole responds to environmental signals and how it interprets those signals (Kull, 2005).

In GAs, gene migration and genetic drift are often overlooked. These algorithms typically focus on deterministic processes that are controlled and predictable (Chen, Li, 2012). Overlooking genetic drift can lead to the loss of rich semiotic interactions that characterise biological evolution. Additionally, GAs, like other heuristic methods, rely on approximation techniques to find solutions to complex problems, which may further limit their ability to capture the full complexity of natural evolutionary processes. Incorporating genetic drift into GAs could involve introducing stochastic changes in solution parameters, simulating random fluctuations in population characteristics.

Biosemiotics and GA

Biosemiotics provides tools for analysing complex natural processes, taking into account contextuality, the meaning and interpretation of signals, and dynamic interactions between organisms and their environment. Integrating biosemiotic perspectives with GAs can lead to more realistic and complex models that better capture the intricate nature of life processes.

Biosemiotics can significantly enrich GAs by adding a semantic and contextual layer to optimisation processes. GAs can be enhanced with a biosemiotic approach by introducing systems of signs and meanings into

the evolutionary process (Hoffmeyer & Kull, 2003). In conventional GAs, solutions are evaluated solely based on their fitness to the objective function. Incorporating biosemiotics would allow for interpreting solutions in the context of their interactions and communication with the environment, potentially leading to more complex and realistic optimisation models.

The concept of Umwelt can be applied in GAs to model how different solutions interpret and respond to their problem space (environment) in the context of an optimisation problem. Each solution (chromosome) in the population can have its unique perception of the optimisation environment. This perception can be modeled using additional parameters or metadata representing how a given solution "sees;; the problem (Uexküll, 1934). Moreover, it would be beneficial to create a dynamic environment that changes over time (Yang, 2005). Solutions can interpret these changes based on their individual perceptions. Solutions can exchange information about their environmental perceptions. For instance, one solution can "teach" another how to better avoid obstacles based on its experiences, similar to social learning in nature (Barbieri, 2001).

Each solution can adapt its optimisation strategies based on its unique environmental perception. For example, a solution that "sees" greater danger from a specific problem area may avoid that area or adopt more cautious strategies.

Fitness evaluations can consider traditional success measures (e.g., minimising objective function) and additional measures reflecting how well a solution adapts to its environmental perception. For example, a solution that effectively navigates a dynamically changing environment may receive extra points for adaptability (Morrison & De Jong, 2000; Yang, 2003).

Biosemiotics emphasises the importance of communication and cooperation among organisms (Sharov et al., 2016). In GAs, this can be implemented through mechanisms that allow different solutions to exchange information and cooperate, potentially leading to better global solutions. An example could be the introduction of symbiotic mechanisms, where different "organisms" (solutions) cooperate for mutual benefit. Solutions can exchange information about their states and fitness results (Watson et al., 2002). Each solution can transmit information about its best features to other solutions, which can help avoid local minima and promote a global optimal solution. It is also possible to introduce symbiotic mechanisms where different solutions cooperate for mutual benefit. For instance, two or more solutions can combine their best features to create a new solution with the potential to be more adaptive than any of the individual solutions alone (Axelrod & Hamilton, 1981; Yong et al., 2008).

An interesting proposal would be to introduce cooperative coevolution, where populations of solutions evolve together, sharing information and adapting to each other. Each solution can adjust its strategies based on information received from other solutions. Implementing ecological role mechanisms, where different solutions play different roles in the optimisation ecosystem, would allow some solutions to explore new areas of the solution space while others focus on exploiting and optimising already found areas. Solutions could adapt their strategies based on signals received from other solutions (Deb, 2000). For example, if a solution receives a signal that another solution has found a particularly advantageous area of the solution space, it can adjust its trajectory to explore that area as well.

Selection processes in GAs can be enriched by the interpretation of signs. Mutations can be guided by semantic signals indicating the need for adaptation to changing conditions. Selection can consider fitness and the ability of a solution to communicate and interact with other solutions. Introducing such selection mechanisms in GAs can involve exchanging signals between solutions (chromosomes) and their "environment" (objective function or other chromosomes), allowing for more adaptive and efficient selection strategies (Fogel, 2006). Chromosomes can exchange information about their fitness and potential mutation directions, similar to how organisms exchange chemical or auditory signals to optimise their survival strategies (Hoffmeyer, 2008). Moreover, implementing multi-channel communication between chromosomes can include abstract representations of chemical, auditory, visual, and tactile signals. Chromosomes can exchange information through virtual "pheromones," leaving traces in the solution space that other chromosomes can follow, similar to ant colony algorithms (Morrison & De Jong, 2000). Auditory signals can be an abstract representation of information, where chromosomes emit sounds of different frequencies, and other chromosomes adjust their strategies based on these signals (Gildenhuys, 2024).

Visual signals can represent spatial information, helping chromosomes effectively direct their actions based on visualisations such as heat maps. Virtual tactile signals can convey information about local gradients of the objective function, allowing for more precise tuning of optimisation parameters. Implementing these mechanisms allows for better modeling of complex interactions and dynamic adaptation to changing problem conditions, leading to more realistic and efficient optimisation models.

In GAs, mutations are controlled and introduced to increase variability and avoid local minima in the search space. However, this approach does not consider the interpretive complexity present in natural systems. To enrich

GAs with this complexity, several innovations can be introduced. Integrating semiotic mutation mechanisms involves considering environmental signals that influence mutation decisions (Fogel, 2006). Algorithms can dynamically adjust mutation rates and locations in response to simulated environmental conditions. An algorithm can increase mutation rates in specific "genome" regions of solutions in response to detected "environmental stresses," such as changing optimisation problem conditions (Sharov et al., 2016).

GAs can introduce adaptive mechanisms that allow chromosomes to respond to changing conditions (Bruno et al., 2018). Chromosomes could communicate their adaptive states, and the algorithm could dynamically adjust mutation rates based on this information. For example, if difficult conditions are detected, the algorithm could increase mutation rates to promote the emergence of new, potentially more adaptive features. Introducing internal signaling mechanisms that influence the mutation process allows for more complex interactions within the solution population (Miikkulainen & Forrest, 2021). Chromosomes could use signals to communicate their condition and adaptive needs, influencing mutation decisions. For example, chromosomes could activate specific defence mechanisms in response to stress signals, increasing mutation rates in specific genome regions, similar to how biological organisms respond to environmental stress (Barbieri, 2001).

The introduction of genetic drift mechanisms can also enrich GAs. Gene migration involves transferring solutions between different populations, increasing genetic diversity and preventing premature convergence. Migration mechanisms can be implemented through periodic exchanges of solutions between different populations, simulating the influence of new genetic material on the population (Deb, 2000). Genetic drift, as random changes in allele frequencies, can be modeled by introducing random changes in solutions, regardless of their fitness values (Kimura, 1983). These changes can affect population diversity and help avoid local minima. Introducing these mechanisms allows for a more realistic representation of natural evolutionary processes and improves the efficiency of GAs in solving complex optimisation problems.

Conclusions

Introducing biosemiotic perspective into GAs is not just a technical innovation but a genuine step toward creating machines that can better understand and adapt to our world. By addressing biosemiotic processes at

both unicellular and multicellular scales, this paper underscores the versatility of biosemiotic frameworks in understanding life processes across diverse biological systems.We see this potential in rescue robots that can navigate chaotic, changing environments more effectively, and in industrial robots that adapt to dynamic production lines. Moreover, incorporating biosemiotics into GAs raises the ethical standards of genetic modifications. By considering the subjective needs of organisms, we can aim for more responsible and sustainable practices that respect the complexity and integrity of living systems. One of the most promising aspects of this integration is the possibility of combining GAs with neural networks, creating systems capable of adapting and learning in dynamic, complex environments. Such a combination could lead to models that mimic natural processes and transcend them, opening new horizons in science and technology.

Integrating biosemiotics with GAs introduces a less reductionist approach, considering contextuality, signal interpretation, and dynamic interactions, leading to more realistic and advanced optimisation models. This approach increases adaptability, population diversity, and optimisation process efficiency while better reflecting the complexity of natural biological processes (Sharov et al., 2016). This allows algorithms to achieve better global solutions, avoiding local minima and dynamically adapting to changing problem conditions (Belciug & Gorunescu, 2013). Biosemiotic mechanisms also extend standard computational models of natural processes, enabling GAs to better reflect the complexity of natural evolution (Goñi-Moreno & Nikel, 2019).

Finally, adopting a biosemiotic perspective in GAs deepens our understanding of nature and computation and prompts deeper reflection on the limits of computability and the nature of intelligence. This interdisciplinary approach, combining philosophy, computer science, and biology, inspires us to explore the boundaries of our knowledge and technological possibilities. In this context, the future of GAs enriched with biosemiotics seems not only promising but also incredibly fascinating.

NOTE

[1] Pancomputationalism, which views every natural process as computation (see Piccini and Maley 2021 for a definition of pancomputationalism), oversimplifies the complexity of natural systems.

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