Memetic computation - past, present future

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Research Frontier
Memetic Computation - *Past, Present & Future*

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I. Introduction

From the word "mimeme" of Greek origin, Dawkins coined the term "meme" in his 1976 book on "The Selfish Gene" [1]. He defined it as being "the basic unit of cultural transmission or imitation". These days, the monosyllabic word "meme" that is an analog of the word "gene" has since taken flight to become one of the most successful metaphorical ideologies in computational intelligence. The new science of memetics today represents the mind-universe analog to genetics in cultural evolution, stretching across the fields of anthropology, biology, cognition, psychology, sociology and socio-biology.

What defines and constitutes a meme? While some believe that memes should materialize as information restricted to the brain, others think that the concept extends to behaviors and artifacts. In the 1999 book "The Meme Machine" [2], Blackmore discussed the roles of gene, meme and their associations, as well as the analogy of gene in serving the instructions for making proteins to meme as instructions for carrying out behavior. Other researchers on the other hand have looked upon memes in different lights, from being "constellation of activated neuronal synapses in memory or information encoded in neural structure" [3], "contagious information pattern that replicates by parasitically infecting human minds" [4], "memory item, or portion of an organism's neurally-stored information" [5], "ideas, the kind of complex idea that forms itself into a distinct memorable unit" [6], "any kind, amount, and configuration of information in culture that shows both variation and coherent transmission", [7], "unit of information in a mind whose existence influences events such that more copies of itself get created in other minds" [8], to "genotype as mental representation, and phenotype as implemented behavior or artifact" [9] and even as "hierarchically arranged components of semantic memory, encoded by discrete neural circuits" [10].

Along with the multi-faceted definitions and roles of "meme" in computational intelligence, a plethora of potentially rich memetic computing methodologies, frameworks and operational meme-inspired algorithms have surfaced in the last decades. In this article, we showcase several successful applications of memetic computing methodologies in solving complex problems in arts, science and engineering. The rest of this article is organized as follows. Section 2 describes the role of hybridization and how it has shaped the first wave of research on memetic computation. More specifically, hybridization in the form hybrid global-local search algorithms for various application areas are discussed and illustrative instantiations of memetic computing for the exploration and optimization of low-energy isomers on the landscapes of molecular structures, particularly water clusters $(H_2O)_n$, and mission path-planning for unmanned aerial vehicle are shown. Section 3 presents an aspect of memetic computing that fulfils some traits of an evolving system by materializing as a form of adaptive memetic algorithm that acclimatizes to suit a given problem in hand. In Section 4, emerging fields of memetic computing with some insightful illustrations on the various manifestations of memes from a computational paradigm perspective are shown. Finally, Section 5 offers an overall broad perspective on the current status of research before summarizing with some concluding remarks in Section 6.

II. Hybridization

In a generic sense, hybridization refers to the mixing of at least two heterogeneous entities either through conscious manipulation or as a natural progressive transformation. When the process is intentionally manipulated, it is usually with the objective of deriving a more superior variant of the two constituent entities. From an algorithmic perspective, two or more distinct methods when combined together in a synergistic manner can enhance the problem-solving capability of the derived hybrid. As such, hybridization is one important feature evident in memetic computing techniques.

Towards this end, the earliest and fastest growing areas of memetic computing research is 'memetic algorithm (MA)' which was coined in 1989 [11] as a form of hybrid global-local heuristic search methodology. There, the global search is usually a form of population-based method, to be more specific, a genetic algorithm, while the local search is said to resemble a meme.

Within the computational intelligence community, research on MA has since grown significantly and the term has come to be associated with the pairing of meta-heuristics or population-based methodologies with separate lifetime learning process that materializes in various forms of individual learning and social learning. To date, almost all successful stochastic optimization algorithms including meta-heuristics and evolutionary algorithms involve some forms of lifetime learning or meme in their design. Such synergy has been commonly referred to in the literature as hybrid evolutionary algorithm, Baldwinian EAs, Lamarckian EAs or genetic local searches. Here, the basic unit of cultural transmission, i.e., meme, is regarded by the computational intelligence community as a lifetime learning procedure capable of generating refinement on given individual(s).

The activities of MA research in the form of hybrids have powered the initial interests and studies of memetic computation research for nearly two decades. Remarkable success on significant instantiations of specialized MAs [12] across a wide range of application domains have been reported, ranging from NP-hard combinatorial problems such as quadratic assignment [13], permutation flow shop scheduling [14], VLSI floor planning [15], gene/feature selection [16], travelling salesman [17], scheduling and routing [18], multidimensional knapsack [19], to non-linear programming problems including aerodynamic design [20, 21], atomic and molecular structure problems [22], optimal control systems of permanent magnet synchronous motor [23], data-mining, machine learning and artificial neural networks [24], dynamic optimization problems [23, 25], computationally expensive environments [20, 26], robust design [26], fuzzy modeling [27, 28], and multi-objective memetic search [29-33].

Two examples of successful MA deployments are shown in Figures 1 and 2. The first depicts the successful application of MA in the discovery of low-energy stable molecular structures [22] and the second shows the mission path-planning for unmanned aerial vehicle (UAV) [17].

| Iteration 1 | Iterations 302 | Iterations 505 | Local Minima converged at Iterations 1243 |

1(a)

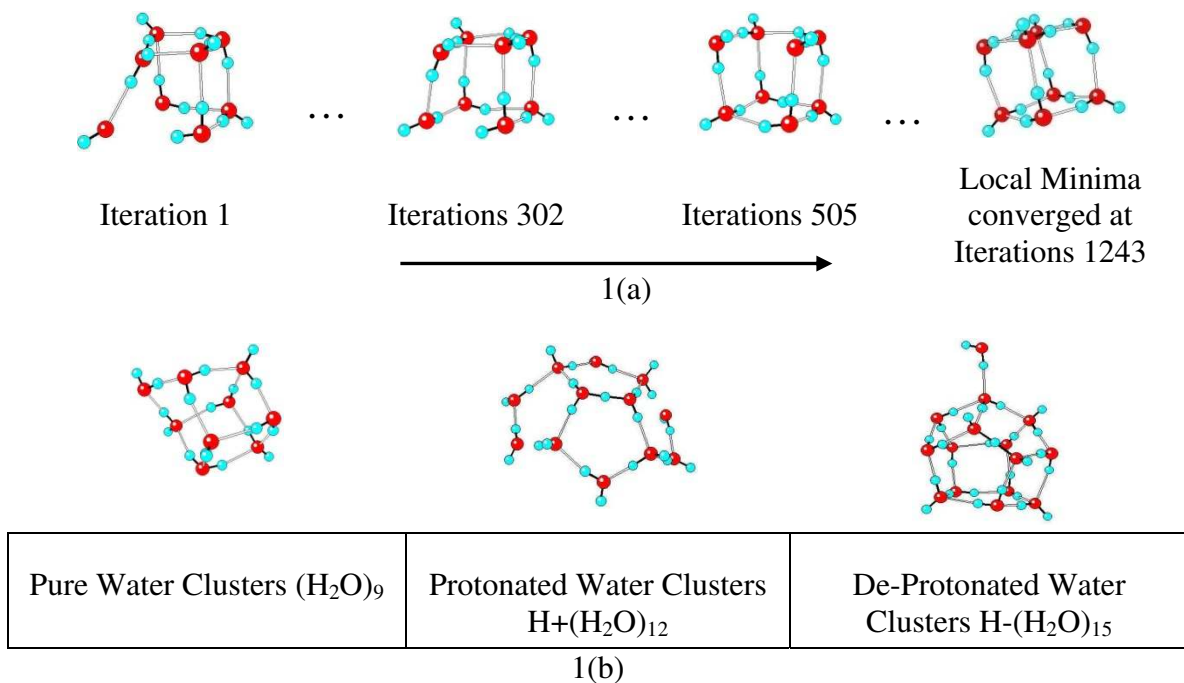| Pure Water Clusters $(H_2O)_9$	Protonated Water Clusters $H+(H_2O)_{12}$	De-Protonated Water Clusters $H-(H_2O)_{15}$

1(b)

Figure 1: (a) Topological configurations of $(H_2O)_8$ using OSS2 semi-empirical model while BFGS as lifetime learning or local search procedure; (b) Global optima water molecular structures [22].
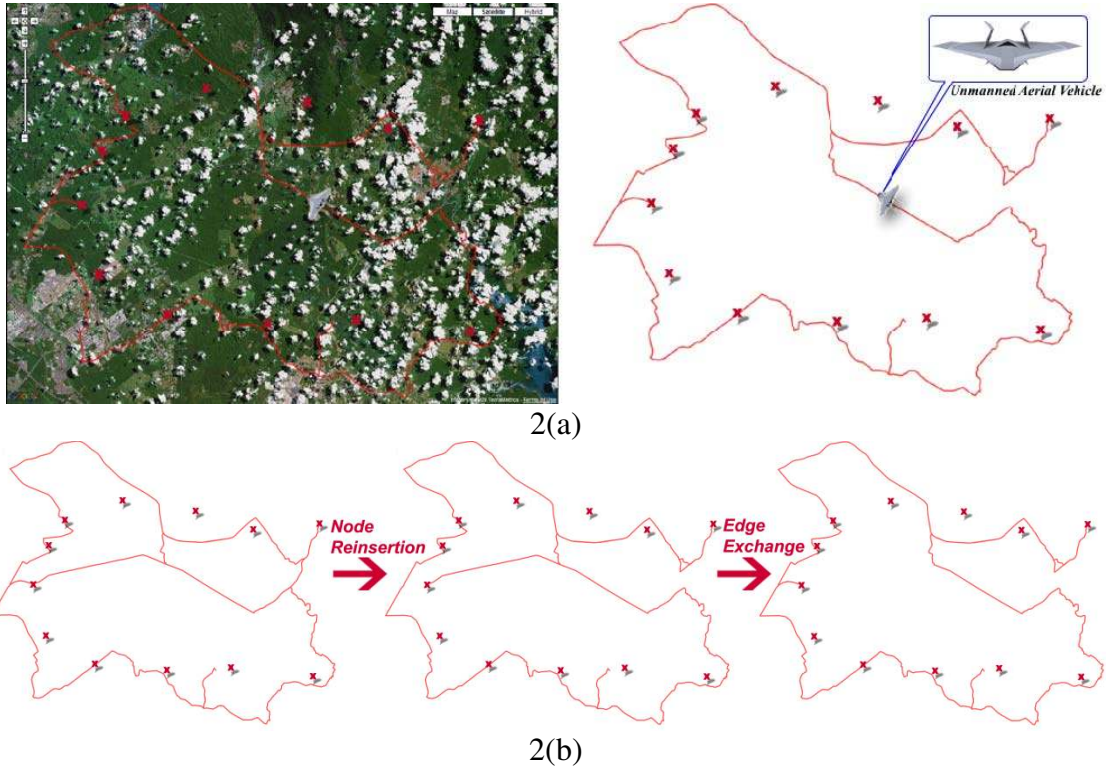
2(a)

2(b)

Figure 2: (a) Unmanned aerial vehicle (UAV) path planning in reconnaissance mission; (b) Local heuristics for refinement of UAV path [17].

III. Hybridization with Adaptation

It is well established that depending on the property and complexity of a problem, computational methodologies that may have proven to give performance advantage on a particular class of problems can only be achieved by accepting a tradeoff in performance degradation on other classes of problems; an outcome that is consistent with the "no free lunch theorem" [34]. The theorem has served as a key driving force of computational intelligence research for more than a decade where a plethora of dedicated MAs have been manually crafted by system developers to solve domain-specific complex problems. The incorporation or embedding of knowledge about the underlying problem within the search algorithms is now generally accepted as being beneficial for improving search performance [35, 36][37] . It is worth noting that while it is possible to use existing search methodologies for general black-box optimization, it comes with the disadvantage of performing less competitively compared to problem-specific approaches.

In the new millennium, the general practice of manual crafting of dedicated MAs in the computational intelligence community has evolved into the emerging field of adaptive memetic algorithms. Adaptation of parameters and operators in MA represents one of the most important and promising areas of research in computational intelligence. They are self-configuring algorithms capable of acclimatizing to suit a given problem in hand, by methodically utilizing acquired information about the matching of problems to procedures, and reconfiguring itself to adapt to the problem as the search progresses. Within this growing trend, some researchers have focused on studying the design issues

of MA that maintain good balance between exploration (population-based) and exploitation (lifetime or individual learning) throughout the search, for general or particular classes of problems via empirical and theoretical studies. In particular, it is now well-established that potential algorithmic improvement can be achieved by adapting several key design issues of MA as listed here:

1) How often should lifetime learning or local learning be applied, i.e., local search frequency? [38, 39]
2) What is the appropriate probability for applying lifetime learning or local learning to an individual? [39, 40]
3) To which solution subset of the population should the lifetime learning or local learning be applied? [23, 39]
4) How long should lifetime learning or local learning be conducted, i.e., local learning intensity? [39]
5) How to alleviate the potentially high computational cost incurred by lifetime learning, especially when dealing with real world complex problems plagued with computationally expensive cost functions? [20, 26]
6) What form of lifetime learning or local learning methods or otherwise referred to as meme(s) to use? [37]

In addition, researchers are now seeking adaptive memetic methodologies that satisfy partially all three principles of a 'truly' evolving system, i.e., *heredity*, *variation* and *selection* as defined by the theory of Universal Darwinism [1]. This includes multi-meme MA [41], hyper-heuristic [42] and meta-Lamarckian MA [43, 44], co-evolution and self-generation MAs [45], multi-agent memetic computing [46]. For a discussion on the various forms of MAs inspired by Dawkins's theory of Universal Darwinism or a taxonomy and comparison of some early adaptive memetic algorithms, the reader may refer to [43] and [37], respectively.

In Figure 3, an illustration of self-configuration within a search algorithm; an adaptive memetic approach for solving the classical NP-hard vehicle routing problem, is provided. It depicts ADEP, an Algorithm Development Environment for Problem Solving, designed as a platform for the self-configuration of memetic solvers. For a detailed discussion on ADEP, the reader may refer to [47].

3(a)

4 vehicle routes | 5 vehicle routes | some demands moved from blue route to pink route
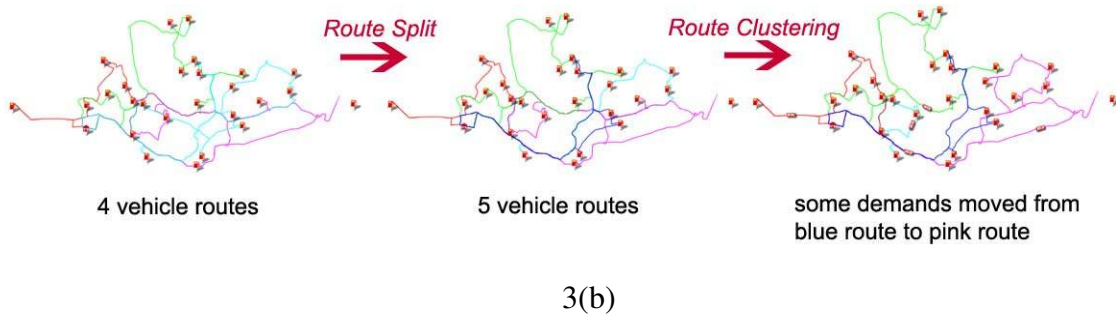
3(b)
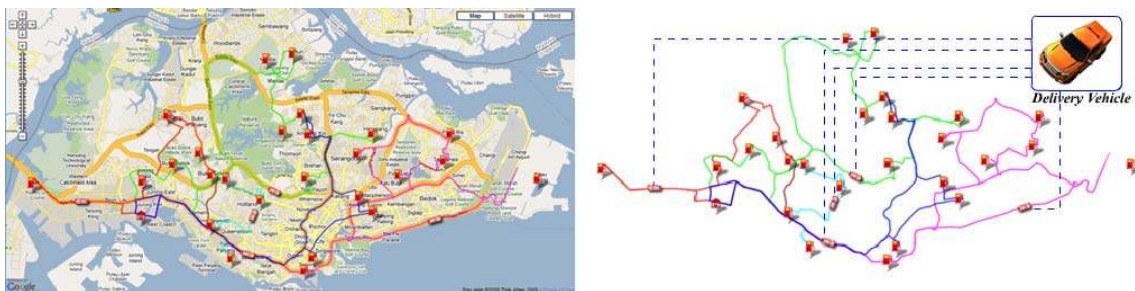
Figure 3: (a) ADEP-configured adaptive memetic solver for the VRP implemented on the ubiquitous Google map environment; (b) Dynamic configurations of vehicle routes using ADEP-configured local heuristics.

IV. Contemporary Definitions of Memes in Computational Intelligence

In a sociological context, 'meme' has been loosely defined as the basic unit of cultural information [1, 2]. In this section, we discuss several recent and potential realizations of meme that serves to benefit the field of computational intelligence. To resolve the potential confusion that may arise due to the unavoidable close association with memetic algorithm, a more explicit definitive statement about 'memetic computation' is warranted. In particular, we define 'memetic computing' as a *paradigm that uses the notion of meme(s) as units of information encoded in computational representations for the purpose of problem-solving*.

A. Memes as Recurrence of Patterns

A good problem-solving technique besides being scalable should ideally exhibit consistent performance over a wide range of characteristically different problems in the domain that it is intended to handle. In the process of solving a repertoire of problem instances, memes can *culminate from recurring information patterns or structures*. From basic patterns or structures, more complex higher level structures are evolved. In our recent work [48], a brain inspired meta-learning memetic computational system, consisting of an optimizer, a memory, a selection mechanism, and a generalization mechanism that conceptualizes memes not just within the scope of a problem instance, but rather in a more generic contextual scope was demonstrated. The aim is to alleviate a major drawback of present computational intelligence search methods which usually start from zero information independent of the similarity between problem instances or domains encountered in the past. In particular, the system establishes inter-instance and intra-instance memory from past problem instances solved and provides learning [49, 50], selection and generalization capacities that draw on these memories to search more effectively and efficiently. It is noted that for many real-world problem domains, complex problem instances are composed of smaller, less complicated problem instances or low order structures characteristic of the smaller problems. The methodology was subsequently applied on the classical even parity and travelling salesman problems. In the former, the discovery of an XOR concept/operation from a simple 2-bit problem instance

was stored in an inter-instance memory and subsequently used to guide the optimization method in solving higher complexity n-bit even-parity function more efficiently.

B. Memes as Contagious Information Pattern in Style Art

Taking a philosophically *memetic* perspective in computational intelligence approach to stylistic non-photorealistic rendering (NPR) [51], a meme or stylistic expression can cognitively evolve by a process akin to natural selection, a primary mechanism that drives Darwinian evolution. NPR is the challenge of transforming a camera-captured digital image of something real into a pictorial rendering that is either conventional or something novel. A style is thus defined as *an idea or concept or meme that can be transmitted via demonstration and learned by communication*. Memes compete to be selected for use and replicate as units of transmission based on selective success. In the "style discovery" phase of artistic expression and production, *memes* or *memotypes* [2, 4] are being explored, rejected and recombined. Style learning and generalization mechanisms are provided to capture memes, i.e., the essence of knowledge in the form of instructions, which affect the transitional stages of the visual arts. New memes inherit combinations of traits of their ancestors while also being subjected to random variation. Stylistic meme can then be represented operationally, i.e., in a manner that allows the meme to be manifested in digital images while they are being created. The newly found memes may then be used to generate art assets that embody the style at "style production".

Figure 4 illustrates an instance of the contagious stylized representation (*memotype,* analogous to genotype in genetics) [51] and their expressed form (*sociotype,* analogous to phenotype in genetics) as digital image representations. Here, *memes* or *memotype* are encoded in the form of instructional schemata for creating art styles such as pointilism, impressionism, cubism, painterly, sketchy, or other novel styles.
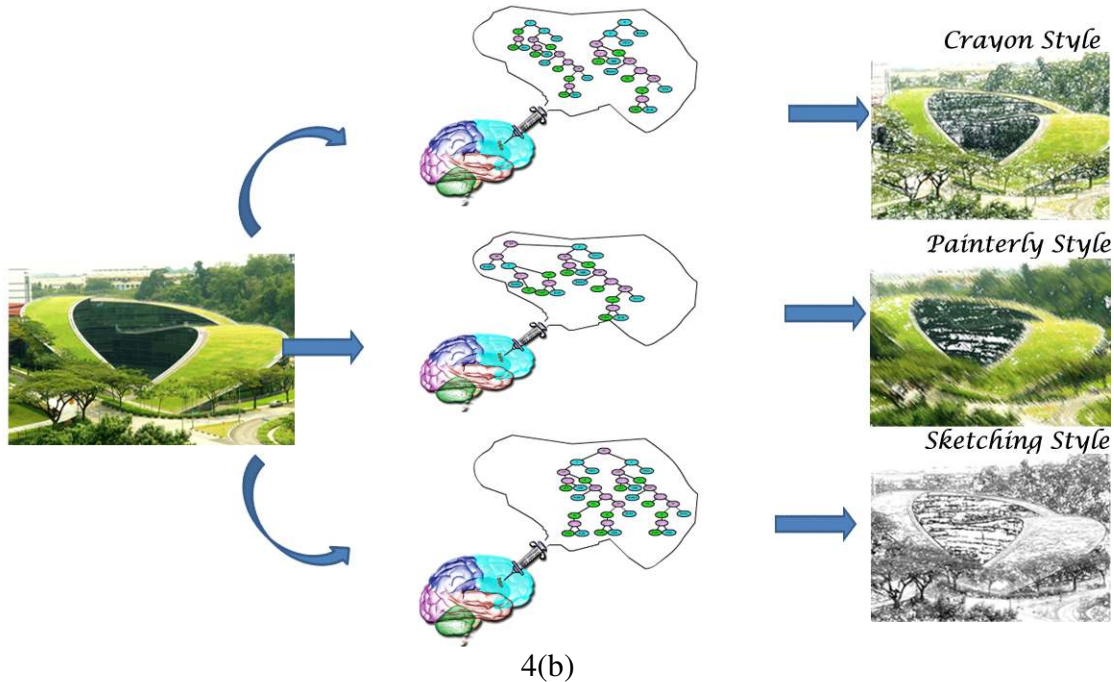

4(a)

4(b)
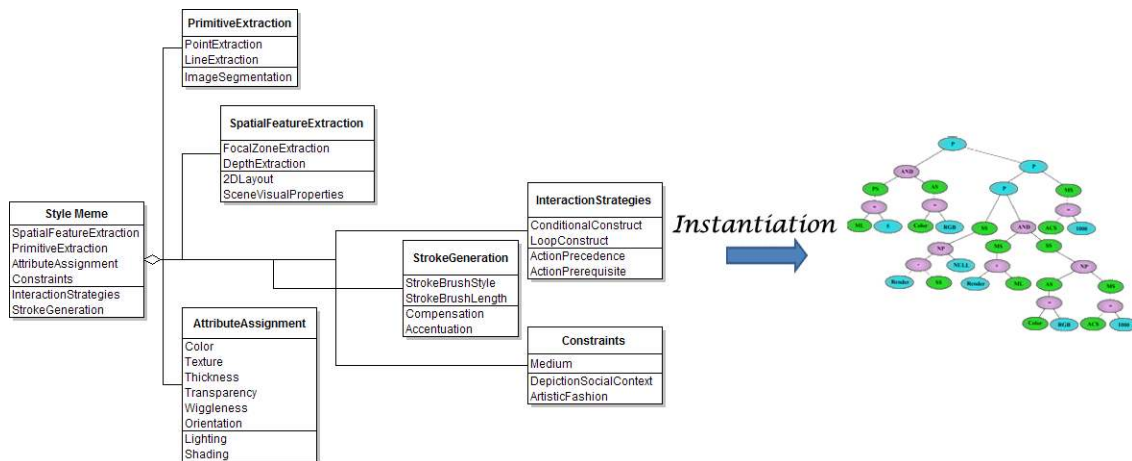
Figure 4: (a) Style *memes* or *memotypes* as instructional schemata representations composed of basic drawing primitives and operations parameterized by location, size, orientation, shape, brightness/luminance, color, texture, variance and others that define styles [51]; (b) Expressed *Memotypes* and their corresponding *Sociotypes*.

C. Towards Human-like Intelligent Agents

Meme-gene coevolution offers a natural approach for the development of intelligent agents. By distinguishing meme and gene as two separate replicators, a co-evolving system of intelligent agents may emerge. In the process, the complex and dynamic interactions or association between the two replicators can deepen our understanding of human origins as a cultural species, hence offering useful leads towards the design of truly human-like intelligent agents.

In biology, the interaction or association between two species has been established in the form of mutualism, commensalism, amensalism, or parasitism [3]. Clearly, what is beneficial to genes may be detrimental to memes in a competitive interaction arena or vice versa, i.e., parasitism. It may also be that memes interact with genes to enhance each others' survival and reproduction, i.e., mutualism. Working in synergy, the genetic subsystems may also serve as a vehicle for the memetic system which defines the control and reproduction mechanisms of the genetic subsystems, thus forming higher order systems with new memetic and genetic factors emerging within the agent, mutually interacting at various levels of control and reproduction structure.

In practice, the agent model may composed of a number of genetic subsystems involving sensory, reflectivity, reactivity and other factors, whose survival is dependent on the survival of the system at the cultural level. On the other hand, the culture system may

include various memes involving emotion, personality, strategy and other human factors. In this sense, the memetic system operates at higher level while the genetic subsystem at the individualized component level. Figure 5 presents a memetic multi-agent simulation system composing of socially intelligent agents and the instantiations of gene and meme in computing agents; memes can be encoded as unit of schemata information, neurally-stored information (i.e., a connectionist representation of meme), fuzzy rules representation or captured as graph structures. In the simulation, agents participate in a *Swiss system tournament*, with the objective of destroying enemy forces under a *fog of war* condition. The environment elements such as terrain, weather, and water body are randomly generated during each tournament. An agent has physical capability, for example weaponry, armor, aiming precision etc., which are upgraded through genetic evolutionary processes. Throughout a tournament, agents also learn and communicate *experienced* or *enacted* shared information from the environment [52, 53] as well as from the process of engaging the enemies in combat. As shown in Figure 5 (b), in the communication process, memes serving as units of encoded information are transmitted, processed, manipulated and incorporated into the agent's sense of the world.

5(a)
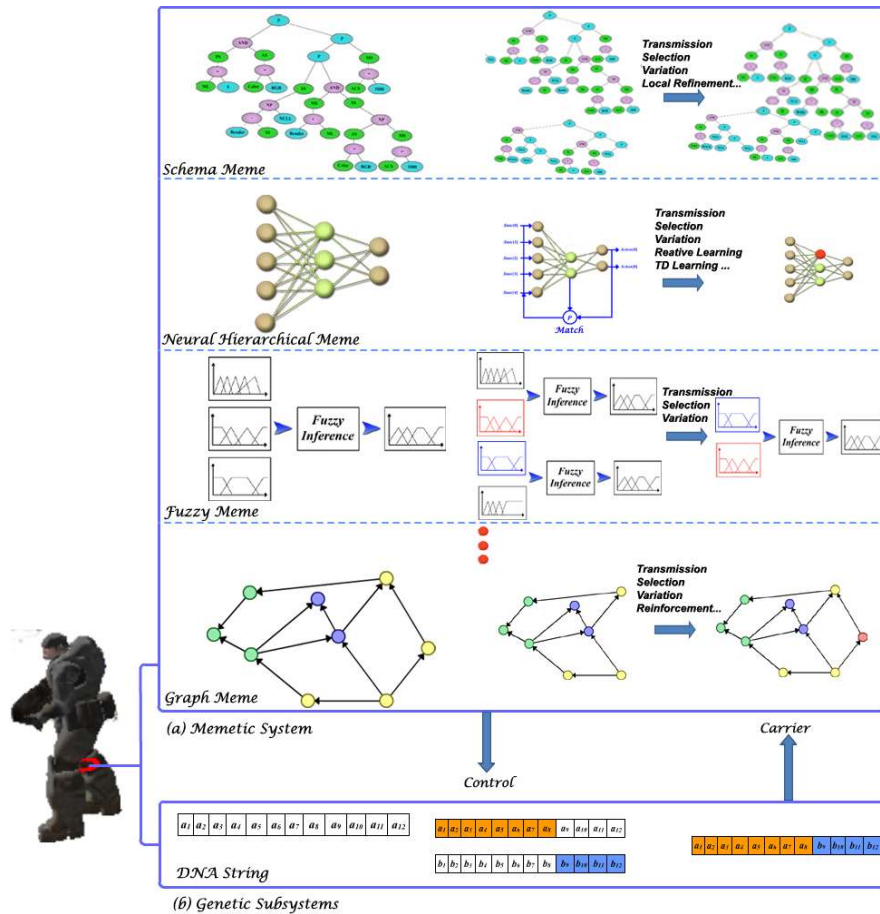
5(b)

Figure 5: (a) Memetic multi-agent system composing of socially intelligent agents using a meme-gene coevolution paradigm; (b) Instantiations of gene and meme in computing agents.

V. Academic and Industrial Activities

Interest in memetic computation in the last two decades shows an increasing trend as demonstrated by the significantly increasing research publications in many top quality computational intelligence and soft computing journals [25, 54-56]. More specifically, an exponential increase in the number of research publications have been revealed in the ISI Web of Science database with the top three most cited papers having appeared as IEEE Transactions publications [44, 57, 58]. Special sessions on memetic algorithms have consistently been organized in the annual IEEE Conference on Evolutionary Computation (CEC) and bi-annual IEEE World Congress on Computational Intelligence by members of The Task Force on Memetic Computing in the IEEE Computational Intelligence Society Emergent Technology Technical Committee since its inception in 2006. In 2009, two special sessions on memetic algorithms have been organized with similar plans made for WCCI'10 and SSCI'11. The surge in memetic computation research is also evident

through the special issues on Memetic Algorithms in IEEE Transactions on Systems, Man and Cybernetics - Part B [54] and Soft Computing [55] journals, including the recently announced special issue for IEEE Transactions on Evolutionary to report on the recent advances of memetic computation. Edited book volumes on memetic algorithms [25] and multi-objective memetic algorithms [56] as well as a new journal Memetic Computing [36] have also emerged recently, highlighting the significant growth in interest.

While academic activities are more straightforward to monitor, it is a different story for industrial-driven activities. There are however clear signs that industrial-oriented research in this field has gathered pace in recent years. Funding from companies such as ST Engineering, Boeing Research & Technology, Rolls Royce Advanced Technology Centre and Honda Research Institute are indicative of the fact that industries are keen on harnessing the potential of memetic computation in solving real-life practical problems. For example, in the past couple of years, ST Engineering has been funding an initiative to develop a logistic planning platform for managing the mobilization of vehicles between locations. We therefore expect research in this field to intensify with industrial participations as the main driving force in the years ahead.

VI. Conclusions

Taking a lead from the multi-faceted definitions and roles of the term "meme" in memetics, a plethora of potentially rich memetic computing methodologies, frameworks and operational meme-inspired algorithms have been developed with considerable success in several real-world domains in the last two decades. In this article, we have showcased several successful deployments of memetic computing methodologies for solving complex problems, from science, engineering to digital arts.

Today, the term 'memetic algorithm' has come to be associated with the algorithmic pairing of a global search method with one or more local search methods. In a sociological context, a 'meme' has been loosely defined as a unit of cultural information, the social analog of genes for individuals. Both of these definitions are inadequate, as 'memetic algorithm' is too specific, and ultimately a misnomer, as much as a 'meme' is defined too generally to be of scientific use.

Memetic computing offers a broader scope that captures appropriately the essence of existing and potential work in the field. It is defined *as a paradigm that uses the notion of meme(s) as units of information encoded in computational representations for the purpose of problem-solving*. As illustrated in this article, representations in the forms such as decision tree, artificial neural works, fuzzy system, graphs, etc., are examples of various manifestations of memes encoding. In this respect, the expanse of memetic computing remains largely untapped and judging from the research activities devoted to this area in the last few years, it is a matter of time before we see more demonstrative and ground-breaking applications in this rich research arena.

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