Complex Adaptive Systems

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Abstract- **The field of Complex Adaptive Systems (CAS) is approximately 20 years old, having been established by physicists, economists, and others studying complexity at the Santa Fe Institute in New Mexico, USA. The field has spawned much work, such as Holland's contributions of genetic algorithms, classifier systems, and his ecosystem simulator, which assisted in provoking the fields of evolutionary computation and artificial life. The framework of inducted principles derived from many natural and artificial examples of complex systems has assisted in the investigation in such diverse fields of study as psychology, anthropology, genetic evolution, ecology, and business management theory, although a unified theory of such complex systems still appears to be a long way off. This work reviews the principles of complex adaptive systems as a framework, providing a number of interpretations from eminent researches in the field. Many example works are cited, and the theory is used to phrase some ambiguus work in the field of artificial immune systems and artificial life. The methodology of using simulations of CAS as the starting point for models in the field of biological inspired computation is postulated as an important contribution of CAS to that field.**

Keywords- Complex Adaptive Systems, CSA, General Principles

I. INTRODUCTION

Complex Adaptive Systems (CAS) refers to a field of study and resultant conceptual framework for natural and artificial systems that defy reductionist (top-down) investigation. Such systems are generally defined as being composed of populations of adaptive agents whose interactions result in complex non-linear dynamics, the results of which are emergent system phenomena. As a field of study, CAS is concerned with (1) comparing natural and artificial examples of CAS to distil general properties and processes and (2) investigate computer simulations of simplified models of natural systems. CAS provides a conceptualisation and framework for a class complex systems and their resultant phenomena providing both computational tools and inducted principles. The field is inherently interdisciplinary, drawing strongly from complexity science, systems theory, control theory and network theory, and weakly from related fields such as statistical mechanics, artificial intelligence, game theory, and optimization.

There are many ways consider complexity and to address complex systems, and the framework of complex adaptive systems is but one conceptualisation. Anderson [43] provides an insightful summary of eight popular theories or 'ways' of thinking about complexity, which highlights the diversity of such approaches.

1. Mathematical – modern complexity theory of Turing and von Neumann, the lemma-theorem-proof structure. The so called theory of complexity of modern computer science which includes the contribution of complexity classes (NP completeness).

2. Information Theory – Measures of complexity and information in Hamming space as bits in terms of order and randomness. Called a theory of limits, for example cannot hold more bits than the number of synapse in our natural network.

3. Ergodic Theory – The study of dissipative dynamical maps including orbits, attractors, and deterministic dynamical systems. Includes chaos theory and bifurcation theory.

4. Artificial Entities – The study of artificial entities in computers such as cellular automata (CA). Such work results in simulations such as the game of life, and the theory of 'edge of chaos' in which complexity may be at its highest between randomness and regularity.

5. Large Random Physical Systems – Systems that have statistical mechanics of complexity with complex high-dimensional attractors. These systems are typically non-ergodic such as random manifolds, percolation, localisation, spin glass and neural networks. Also includes Kauffman's fitness landscape conception of complex systems (rather than attractors) in the context of biological evolution.

6. Self-Organised Criticality (SOC) – Systems in which are driven by some conservative quantity uniformly at a large scale, are able to dissipate it only to microscopic fluctuations, have fluctuations at all scales (as opposed to cycles of stability or system failure, although the systems are not considered adaptive). The systems lead to random fractals of state and scaling laws for the distributions of avalanches.

7. Artificial Intelligence (AI) – To investigate complex adaptive systems by building them. The example provided is an expert system, Holland's adaptive systems such as genetic algorithms and classifier systems.

8. Wetware – The attempt to investigate complex adaptive systems by studying them. The attempt to understand how complex systems like the brain work without attempting to specify a set of underlying principles. The naturist approach of studying systems.

Figure 1 - Summary of Anderson's eight paths to complexity theory

COMPLEX ADAPTIVE SYSTEMS

The study of Complex Adaptive Systems (CAS) is the study of high-level abstractions of natural and artificial systems that are generally impervious to traditional analysis techniques. Macroscopic patterns emerge from the dynamic and nonlinear interactions of the systems low-level (microscopic) adaptive agents. The emergent patterns are more than the sum of there parts, thus the traditional reductionist methodology fails to describe how the macroscopic patterns emerge. Rather, holistic and totalistic investigatory approaches are applied that relate the simple rules and interactions of the simple adaptive agents to their emergent effects in a 'bottom-up' manner.

Generally, examples of CAS are drawn most systems studied in biology, sociology and economics. Some often cited examples include: the development of embryos, function of the adaptive immune system, ecologies, genetic evolution, thinking and learning in the brain, weather systems, market economies, trading systems, social systems, cultures, politics, traffic systems, insect swarms, the flocking of birds, implementation of new ideas, the testing of scientific theories, and bacteria becoming resistant to an antibiotic.

As mentioned, computer simulated models play a large role in investigating CAS where the system is reduced to its simplest essential aspects. These simulation models themselves demonstrate the traits of complex adaptive systems and thus provide a fertile ground for controlled experimentation. Some modelling approaches used and developed for this purpose include cellular automata (CA), agent-based models (ABM), artificial neural networks (ANN), genetic algorithms (GA), and learning classifier systems (LCS).

A. *A Note on CAS History*

The field of complex adaptive systems was founded at the Santa Fe Institute (SFI) in New Mexico, USA, in the late 1980's (perhaps the SFI meeting on complexity in economics in 1987, proceedings: [44]) by a group of physicists, economists, and others interested in studying complex systems in which the agents of those systems change.

Perhaps one of the largest contributors to the inception of the field from the perspective of adaptation was John Henry Holland. Holland was particularly interested in adaptive systems from the perspective of genetic evolution [17]. He conceptualised an 'adaptive plan', which was the progressive modification of structures by means of suitable operators. From adaptive plans, he was interested in the question of how computers could be programmed so that problem-solving capabilities are built up by specifying: "what is to be done" rather than "how to do it". A specialisation of his adaptive plan called the 'genetic plan' ultimately contributed to the founding of the field of genetic algorithms and evolutionary computation. In the 1992 reprint of his book, he provided a summary of CAS with a computational example called ECHO. His work on CAS was expanded in a later book [16] which provided an in depth study of the topic. He also released yet another related work on theories of emergence and rules for emergent phenomena [18].

The study of complex adaptive systems was undertaking intensely at the SFI throughout the early to mid 1990's resulting in the release of many books and papers. A few of more popular works are listed. Waldrop [38] provided a detailed review of the science of complexity, self-organisation, and adaptation recounting the history and inception of the field of CAS and its main findings. Gell-Mann [40] also produced a seminal work on complexity theory including many detailed illustrative examples. Also of note are two seminal edited volumes on CAS [9] and [39].

B. *Definition by Inducted Principles*

There is no clear definition of a complex adaptive system rather sets of parsimonious principles and properties, with, in many cases, different researches in the field defining their own nomenclature [41]. This section lists some common and regarded interpretations of such general principles.

In Chapter 10 of the 1992 reprint of his book [17] Holland provided a preliminary outline of the similarities and difficulties of complex adaptive systems.

Nonlinear Interactions – A large number of individual parts undergoing simultaneous nonlinear interactions where the emergent behaviour is more than the some of the parts.

Aggregate Behaviour – The impact of the system is its aggregate behaviour, the behaviour of the system as a whole, which is often feed back to the parts modifying their behaviour

Change – Interaction of the parts evolves over time and the parts may face perpetual novelty. These systems typically operate far from global optimum and far from equilibrium.

Anticipation – In adapting to changing circumstance, the parts anticipate the consequences of their responses. The aggregate anticipation affects the systems behaviour and this is the least understood property of such systems.

Figure 2 - An early proposal of the general principles of CAS by Holland

Holland suggests three reasons as to why CAS may be difficult to study with conventional approaches: (1) The systems lose the majority of their features when the parts are isolated. (2) The systems are highly dependant on their history making it difficult to compare instances and derive trends. (3) They operate far from global optimum and points of equilibrium making them hard to assess with conventional approaches that are concerned with 'end points' of systems.

Holland goes on to stress the need for a unified theory of complex adaptive systems, and suggests that the framework for such a theory could be built with the mechanisms of *parallelism*, *competition*, and *recombination*. He also suggests that such systems respond instance-by-instant [14], and the importance of the systems ability to balance exploration (acquisition of new information or capabilities) with exploitation (efficient use of information or capabilities already available). In a detailed extension and elaboration on his contribution towards a theory of CAS [16], Holland suggests 4 properties, and 3 mechanisms, which a CAS must possess, which have become a de facto template for phrasing a system as a CAS.

Aggregation – (*property*) Complexity emerges from the interaction of smaller components, which themselves may be the products of systems.

Tagging – (*mechanism*) Agents are differentiated and posses a manner in which to discriminate agents with particular properties.

Nonlinearity – (*property*) Agents interact in dynamical and non-linear ways

Flows – (*property*) Agents organise into networks of interaction in which one interaction may trigger (flow) following interactions.

Diversity – (*property*) Agents evolve to fill diverse niches, which are defined by the specifics of agent interactions. The concept of a niche outlives the inhabiting agents, and the evolution of niches has a larger impact on the system than the evolution of agents (levels of abstraction and control).

Internal Models – (*mechanism*) Agents are changed through there interactions, and the changes bias future actions (agents adapt). The internal representations possess information as how to exploit the regularity of their interactions, without necessarily explicitly defining that regularity.

Building Blocks – (*mechanism*) Components are reused for multiple purposes.

Figure 3 - A paraphrase of Holland's seven aspects of a CAS

Gell-Mann [39,40] differentiates his definition from Holland's by suggesting that Holland's CAS must have a collective of interacting and adaptive agents, where his definition states that each one of Holland's agents is considered a complex adaptive system. In [39], Gell-Mann specifies a cycle for CAS which is composed of six core elements and four concerning issues. He goes on to detail a series of questions related to investigating each point.

1. Coarse graining – trade-off between the *coarseness* for manageability of information and *fineness* for adequate detail in information

2. Identification – sorting out of regularities from randomness in information from the environment

3. Compression – perceived regularities are compressed into a schema

4. Variation – variation and improvement of schema (adaptation or evolution)

5. Application – use of schema to the systems environment, also considered decompression of schema

6. Selection – the consequences of selective pressures in the real world providing feedback and affecting competition for schemata

Issues – issues related to the six aspects of a CAS lifecycle include: (1) time scales, (2) the system included as a component in other systems, (3) systems with humans in the loop, and (4) system composed of many other co-adapting systems.

Figure 4 - Summary of Gell-Mann's lifecycle and related issues of a CAS

Arthur [63] proposes a definition of complex systems as studied in economics with six properties, although refers to such systems (as he claims Holland would) as 'adaptive nonlinear networks'. These properties, like Holland's, are also cited as standard CAS principles.

Dispersed Interaction – Emergent effects are the result of the actions of many dispersed, possibly heterogeneous, agents acting in parallel. The action of an agent is dependant on the anticipated actions of a limited number of other agents, and the aggregate state the limited set of agents create

No Global Controller – No global entity controls interactions, rather controls are provided by competition and coordination between agents. Economic actions are mediated by the rules of the environment.

Crosscutting Hierarchical Interaction – A system has many levels of organisation of and interaction. Units at any level of abstraction within the system serve as 'building blocks' for constructing units at high levels of abstraction. The interactions are more than hierarchical with tangled and crosscutting concerns.

Continual Adaptation – behaviours, actions, strategies and products are revised continually as the individual agents accumulate experience, the system constantly adapts.

Perpetual Novelty – The changes introduced by adaptation continually create new opportunities for exploration, the result is ongoing, perpetual novelty

Out-of-equilibrium Dynamics – Because of the continual change and adaptation, the system operates far from global optimum and equilibrium. Improvements are always possible and regularly occur.

Figure 5 – A paraphrase of Arthur's six aspects of adaptive nonlinear networks

Dooley [21] provides a condensed definition of CAS. In his definition, agents are the base elements of the system that adapt in response to interactions. The adaptations that occur operate upon agent schema, a representation that defines agent rules and interactions. Agent fitness is optimized locally relative to the local microenvironment. The flow of information is non-linear. Agents are tagged (perhaps heterogenous function) and aggregates of heterogenous agents can form meta-agents.

Levin [52] in his phrasing of ecology and the biosphere as a CAS acknowledges Arthur's principles (as well as Holland's 4 properties), although distils them into three essential aspects.

Diversity – sustained diversity and individuality of components

Local Interactions – localised interactions between components

Selection – An autonomous process that selects from among components a subset for replication or enhancement, based on the results of local interactions amongst components

Figure 6 - Three essential elements of CAS distilled by Levin from Arthur

C. *Features and Relations*

Levin [53] summarises CAS and reviews some of the mathematical challenges in the field, in particular unsolved problems of pattern recognition, and the dynamics of system innovation related to the mathematics of ecology and population biology. He cautions the limited predictability of results from simulation to the natural systems. Jost [19] suggests that the environment in which a CAS exists is more complex than the CAS itself and that CAS depends on regularities in its environment. Jost goes on to provide a rigorous assessment of CAS in the context of *internal* and *external* complexity. External complexity is defined as the amount of input, information, energy the system obtains from the environment. Internal complexity is the complexity of the internal representation of the information it takes as input (model complexity). The goal of the system is to handle as much input as possible, as simple model as possible, to attempt to increase the external complexity and reduce the internal complexity of the system.

Emergence is an important aspect of CAS, for example Holland devoted a book to the subject [18]. Holland's thesis was that adaptation leads to complexity, that local rules lead to emergent control and order. The trade-off in emergent control is causation at the level of the individual components of the system. Self-Organization is another important aspect of CAS. Kauffman's thesis [59,60] is that in addition to the pressure of selection in adaptation, order can come about from self-organization, so called 'order for free'. In his work on developing a theoretical foundation for evolutionary biology, Kauffman [60] also clearly elucidate complex systems in the context of a high-dimensional fitness landscape, a notion now ubiquitous in optimization theory.

The continuous adaptation in a CAS may be seen as a trade-off between too much rigidity in the face of change and too much change in the face of achieved progress (a re-phrasing of the exploration-exploitation duality). Work by Langton [3] coined the phrase 'edge of chaos' describing complex systems as operating at critical points at the fringe (a phase transition away) from randomness. While disputed by in the context of some experimentation (such as [36]), the theory highlights the potential fragility of these system, that a crash or failure may occur given an ineffective holistic system response.

II. A Sample of Works

This section highlights some seminal and interesting works on both phrasing natural systems as complex adaptive systems, and computational investigations on the theory of such systems.

Ecology is the study of systems of living organisms, and has proven a prototypical example of CAS. Levin [52] phrases ecology and the biosphere as complex adaptive systems in the complex of Holland's four properties, Arthur's six properties and Levin's own three distilled properties. Bonabeau [7] phrases social insect colonies (ant's, termites, etc) as CAS and show's how such systems fit all the properties discussed by Levin for ecology and the biosphere, and stresses self-organization as a critical feature in social insect systems. Hartvigsen, Kinzig, et al. [8] discuss the convention of systems theory in ecology and phrase ecosystems as complex adaptive systems. They describe the interactions in such systems being either strong and direct or weak and diffuse with positive and negative feedback. They also describe a difficulty of analysing such systems as being the large spatial and temporal scales involved. Railsback [51] applies CAS as it pertains to individual-based modelling (IBM) in ecosystems, as CAS require the modelling of the rules and interactions of individuals to obtain their emergent effects. Sigmund [20] proposes a model of reciprocal altruism in the context of CAS, investigating the evolution of cooperation with computer simulations of the prisoners' dilemma (PD). Finally, Janssen [34] proposed CAS as a way to interpret global change with specific examples of the control of malaria, and climate change.

In his early work mentioning CAS [17], Holland phrased a model ecosystem called ECHO as a computer simulation to investigate complex adaptive systems. This system was elaborated in is later book devoted to the topic [16]. Forrest and Jones [58] investigated CAS using ECHO. They succinctly differentiate complex adaptive systems from complex systems by the adaptive property of their agents (adopting Hollands definition). They also propose that in modelling CAS, it is desirable to strip away as much details as possible and develop models with robust behaviour (not too sensitive to parameters). They investigated broad notions of species abundance in ecosystems with ECHO with results that matched observations. Hraber, Jones, et al. [42] also investigated the abundance of species and species diversity with ECHO, commenting evolution as being a critical component of the model. Smith and Bedau [46] investigated ECHO in the context of Holland's definition of CAS. From their experimental evidence they concluded that the system lacks the diversity of hierarchically organised aggregates to be considered a CAS. Specifically the system supports the genetic diversity without the phenotypic diversity in terms of the emergent ecologies created within the system (trading and combat). They suggest an alternative to ECHO's failure to match the definition, that perhaps Holland's definition was too specialised. They also suggest that perhaps additional features could be added to the simulation to achieve the missing effect. Finally Harris [4] provides an implementation and through treatment of the platform.

Other interesting examples of natural and artificial systems phrased as complex adaptive systems include; organisation change in business (management theory) [22], supply networks [61], technology and innovation theory using patent citation rates [23], the modelling of agent-based computational economies (ACE) [30], analogy making in models of cognition (the copycat system) [35], control of the electrical power grid [1], anthropology [62] and the simulation of artificial societies [11], enterprise application integration (EAI) [12] with business objects as agents, innovation as a steady stream of novelty [15], models of the evolution of language [32], and the relationship between the management of nursing homes and quality of care [31,50].

A final interesting example is that of Goldstone and Sakamoto [45] that in the context of psychology, investigated and measured the transfer of the abstract principles of complex adaptive systems to graduate students using four different interactive scenarios. They claim that given the ubiquity of such systems, and the difficulty in grasping their inter-disciplinary principles, it is important to understand how such principles can be learned. This was in itself addressed as an example of a complex adaptive system.

III. Complex Adaptive Systems and the Immune System

The acquired immune system of vertebrates is an often cited example of a natural complex adaptive system [14,33,58].

Some examples of the acquired immune system phrased as a complex adaptive system include: A simulation of the immune system and the AIDS using a cellular automata (CA) [2]. A simulation of vaccination in the immune system using agents [6]. A general summary of the immune system and simulation approaches in the context of CAS [5]. The simulation of an immune system and HIV using elements of classifier systems, genetic algorithms and cellular automata [13].

There are many models and simulations of the acquired immune system that do not explicitly use the framework of complex adaptive system, although use some of the computational tools (such as genetic algorithms), and terminology (emergence, agents, etc.). Although the literature that matches this definition is vast, there is a pocket of work by Forrest, et al. in the early 1990's, that does match this definition, and whose contribution is clear when interpreted with the CAS framework in mind.

In summary, the work centres on a binary-encoded immune system model to study different aspects of the immune system [54] (inspired by an earlier binary-encoded pattern recognition model of the immune system [10]), which is simulated using Holland-style genetic algorithms. The system demonstrated the ability to: (1) perform pattern recognition in the context of a noisy environment [57], (2) discover and maintain coverage of a diverse antigen population [47,48] (with results similar to some niching genetic algorithms for optimization), (3) to learn effectively in the presence of incomplete information [49], among other contributions.

The ambiguity comes because the work has been phrased in the context of artificial life [37], and computation and pattern recognition [55]. The system was used as the basis for what evolved into 'computer immunology' (the transitional form was a paper by Forrest, Perelson, et al. [56]) to perform pattern recognition for information technology problems such as virus detection and intrusion detection. It is this final perspective, which has blurred the work from a study of artificial life (alife), to that of artificial immune systems (AIS), which in the context of the study of complex adaptive systems, becomes quite clear.

Another body of work, whose contribution is clarified in the context of complex adaptive systems from artificial immune systems, comes from Lee Segel, et al. They propose the acquired immune system as a prototype autonomous decentralised system, a prototype "bottom-up" artificial intelligence [24,29] (and his book on such systems from SFI [28]). As well as his conceptualisation of the immune system as an example of diffuse feedback in a diffuse system [25-27]. It is believed that these models when phrased as CAS may provoke useful starting points for systems in the field of biologically inspired computation for application to engineering and information technology problem domains.

IV. Conclusion

Holland's perspective on complex adaptive systems has been most popular in the field of evolutionary computation, which he assisted in provoking. The genetic algorithm and learning classifier systems are staple Computational Intelligence (CI) techniques for suitable difficult domains such as design, engineering, and pattern recognition. A clear and provoking observation from this divergence, and the Forrest, et al.'s immune system case study is how in both cases the adaptive models assisted to trigger related fields in CI (specifically Biologically Inspired Computation (BIC)). Undoubtedly another example would be the field of artificial neural networks as applied to classification and function approximation, having also derived from CAS models (although before CAS was conceptualised a SFI). This observation was also made by Mitchell in 1993 [33] (and I am sure others) as a viable way of contributing to CI and BIC. Perhaps the diffuse models Segal, et al. could be a case study for such an inspiration.

Finally, it is important again to highlight that although CAS is an interesting and potentially potent conceptualisation, it is only that, and there has been much work in agent modelling, artificial life and computational biology (and other computational variations of physical sciences) that do not acknowledge or conform to the CAS framework. Another potentially interesting extension would be to phrase the acquired immune system as a CAS, and elucidate how this complex biological system conforms to Holland's properties and mechanisms and Gell-Mann's CAS cycle. Conforming the immune system to this framework and to these interpretations specifically may yield additional interesting models to for exploitation in the field of artificial immune systems (AIS).

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