Complex Systems and Artificial Life: A Decade's Overview

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Abstract

Artificial Life models and algorithms are informed by natural and biological processes and phenomena. Artificial Life finds particular use in simulating large, complex systems such as large scale ecosystems or social networks, where the interaction between system entities may give rise to emergent behaviours. Despite the increasing popularity and ubiquitous nature of complex systems, the extent of which artificial life approaches are considered in complex systems modelling and their application across complex systems domains is still unclear. To better understand the overlap between artificial life and complex systems, we conducted a systematic literature review of last decade's artificial life research that had a complex system focus. We performed an automated search of all relevant databases and identified 538 initial papers, with 194 in the candidate set, resulting in 115 primary studies. Our results show that the three most frequent application domains are simulation, followed by social modelling, and biological modelling.We find a plethora of paradigms that can be broadly classified into three main categories, namely, biological, social, and hybrid. We identify the artificial life paradigms that are used to generate the most common complex systems properties as well as a number of research challenges that are critical for the growth of both artificial life and complex systems modelling.

Introduction

Artificial Life is a set of models and approaches adapted and inspired by naturally occurring phenomena and processes (Langton et al., 1989). These paradigms can be applied to a diverse range of problems, such as ecological modelling (Punithan et al., 2011), evolving artificial creatures (Loula et al., 2010), combat simulation (Yu and Zhao, 2010), and modelling application performance in proprietary app stores (Cocco et al., 2014). Complex systems are comprised of autonomous entities with complex behaviours, whose interactions can lead to unexpected and emergent properties (Szabo et al., 2014; Mittal, 2013). Complex adaptive systems (CAS) are a type of complex system where entities and the environment are encouraged to adapt and interact with each other in order to achieve desired properties (Holland, 2006) and provide a more realistic abstraction of real-life scenarios (North et al., 2013). Such systems have become ubiquitous in domains such as social networks, supply chains, health-care networks, smart-cities and smart-grids, the "Internet of Things", and the Internet itself (North et al., 2013).

Artificial life approaches and paradigms can be easily studied and analysed with a complex systems lens, thus allowing a focus on important properties such as self-organisation (Holland, 2006), emergence (Szabo et al., 2014), adaptation (Holland, 2006), modularity (Holland, 2006) and criticality among others. *Self-organization* occurs when entities interact to achieve a specific goal or to move the system in a different state (Holland, 2006; Mittal, 2013). *Emergence* occurs when entities organize to behave collectively, leading to the creation of an unpredictable *macro* state that cannot be decomposed into its *micro* components (Szabo et al., 2014). Some systems can exhibit emergent behavior without self-organization, such as a stationary gas (Mittal, 2013). Emergence has been observed in a plethora of systems, such as communities forming in social networks, formation of ant colonies, and rigid cellular structures (Birdsey et al., 2015). *Autonomy* is exhibited when entities within a system selectively act upon their environment without external control and is fundamental to the demonstration of emergence and self-organisation (Froese et al., 2007). *Adaptation* refers to the individual adaptive processes of system entities and environments as well as to the adaptive ability of the system as a whole (Holland, 2006). When *modularity* is employed, entities or the environment must be comprised of sub-entities that determine the behaviors and actions of the parent entity (Holland, 2006). *Criticality* refers to the time period before the system enters a stable, unstable, or emergent state. In many systems, criticality is observed at the edge of chaos or as a decision point.

Employing a complex systems perspective and considering the above properties explicitly would further the applicability of artificial life paradigms to a variety of domains and would test their use under complex, large-scale scenarios, thus potentially significantly developing the field. Conversely, a better understanding of the artificial life paradigms that would facilitate the appearance of specific complex systems properties will aid significantly in their design, such as, for example, when designing systems with a specific desired emergent property (Mittal, 2013). While a large number of works have looked at modelling complex systems including artificial life paradigms, the extent of their use and applicability is yet unknown. To address this gap, we perform a systematic literature review of artificial life research that had a complex system or complex adaptive system focus.

Related Work

Despite existing literature reviews regarding individual models (Santé et al., 2010), complex system properties (Froese et al., 2007), and artificial life paradigms (Emmeche, 1998), to the best of our knowledge, there has been no review focused on the use of artificial life paradigms in modelling complex systems. In the following we discuss several literature reviews focused on specific artificial life modelling paradigms or applications.

Work by Bedau (Bedau, 2003) analyses established artificial life advances and paradigms up to 2003, providing a rough timeline of artificial life developments starting with Langton's initial seminal work (Langton et al., 1989) and progressing to the then-state of the art advances in evolutionary robotics, swarm intelligence, and evolutionary language modelling. Bedau identifies 13 paradigms, including two that are strongly based on complex adaptive system properties, namely, self-replication and self-organisation, with a discussion that considers the potential applicability of adaptation to future artificial life research, however the study fails to give an in-depth analysis of how complex systems are modelled using artificial life paradigms and approaches.

A study by Bousquet et al. (Bousquet and Le Page, 2004) reviews the application of multi-agent simulations (MAS) to the modelling of ecosystem management. They identify that scientists working in ecosystem management need to examine the interactions between ecological and social dynamics, and that MAS provides a useful model for examining the effects of the convergence of these dynamics.

A later work by Froese et al. (Froese et al., 2007) analyses the use and definitions of autonomy within artificial life applications. The study notes that there is no consensus regarding the definition of 'autonomy' and proposes the introduction of a conceptual distinction between the classes of behavioural and constitutive autonomy. The provided definitions assert that behavioural autonomy relates to the capacity of a system for stable and/or flexible interaction with its environment, whereas constitutive autonomy relates to a system's capacity for autopoiesis, which is considered by the authors to have the undesirable quality of restricting the concept of autonomy to organisms. This classification scheme is used to demonstrate that systems at the date of the study publication (2007) had increased in autonomy over the systems published ten years prior. A review by Sante et al. (Santé et al., 2010) focused on the application of cellular automata models to the simulation of real-world urban processes such as urban planning or modelling urban evolution and described the strengths, flaws, and challenges of using each model for different application domains.

Methodology

Our work aims to identify the overlap between artificial life and complex systems, specifically to better understand how artificial life approaches are considered in complex systems design, modelling, or analysis and conversely whether artificial life approaches consider complex systems perspectives or properties. In the following, we use the term complex systems broadly, to cover both complex systems as well as complex adaptive systems.

Identification of Research

We conducted a systematic literature review by adapting the guidelines proposed by Kitchenham (Kitchenham, 2004) and following a highly structured process that involved (i) an initial trial search to determine selection and exclusion criteria as well as the search string, (ii) relevant database search, (iii) selection of studies, (iv) filtering the studies by evaluating their pertinence, (v) extracting data using our data extraction form and (vi) synthesising the results.

The search terms were applied to the title, abstract, and keyword fields of the ACM Full Text Collection, IEEE Explore, ScienceDirect, SpringerLink and Scopus databases, identifying 68, 19, 433 and 18 papers repectively (538 total). Following our established selection/exclusion criteria discussed below, we read through a target set of 10 papers to determine their inclusion in the set and to calibrate our process. The inter-rater reliability of this process was measured with the Fleiss-Davies kappa (Davies and Fleiss, 1982), which measures the agreement when a fixed set of raters classify a number of items into a fixed set of categories. The Fleiss-Davies kappa for individual classification was 80%, which is considered excellent (Banerjee et al., 1999). In the next stage, we selected the papers that formed the basis for the review. The search results were divided among the authors, who examined each title and abstract, and the corresponding full paper if required, to determine its relevance.

Search String and Inclusion/Exclusion Criteria

The search string used boolean operators to refine the search and was: **(''Artificial Life" AND (''Complex Systems" OR ''Complex Adaptive Systems") AND (model OR analysis))** and was adapted to the specific database. Only papers published since 2008 were considered. The inclusion/exclusion criteria were:

- *Topic* - the paper must design or use, implement, and evaluate at least one artificial life paradigm, and the system under study must be a complex system. Surveys, reviews, and position papers were excluded.
- *Length* $>= 5$ *pages* - short papers were excluded.

- *Language* - only English papers were included.
- *Peer-reviewed* - only papers that have been peer-reviewed were included.
- *Exclusions* - papers that contained only wet- or hardware-based Artificial Life models (without accompanying software-based models) were excluded.

The above search string was formulated to find studies that utilise both Complex Systems and Artificial Life in their design and implementation. The focus on the overlap between complex systems and artificial life means that a range of paradigms that may not have been utilised in conjunction with complex systems were not reviewed.

Data Items

An overview of the data items extracted from the papers is presented below.
Modelling approach - Captures the modelling approached employed.
Analysis approach - Captures the type of analysis used to evaluate the model.
ALife paradigm employed - Captures the artificial life paradigms employed in each paper. These paradigms may include natural or biological behaviours (such as foraging, predation), naturally occurring phenomena (such as ecosystems, evolution, or protein-folding), or social behaviours (such as elections, economic exchange, or semiosis).
Complex Adaptive Systems Properties - Captures any CAS properties that are identified by the paper authors.
Further Applications - Captures whether the paper authors identified any further domains within which the paper topic could be applied.
Scalability Considered - Captures whether the paper authors considered scalability in their analysis.
Challenges & limitations - Captures the challenges or limitations faced by the approach as stated by the paper authors.
Challenge type - Captures the type of challenges identified by paper authors.

Results

We present an overview of the identified data items from the 115 primary studies as well as discuss answers to our research questions.

Application Domains

Our analysis identified 32 unique application domains, 19 of which occurred more than once, as shown in Table 1. 16 application domains occurred only once, such as data mining (de Buitleir et al., 2012), and logistic networks design (Otto and Bannenberg, 2010) among others. The most frequently identified application domain was Simulation (representing nearly 13% of all primary studies), where papers demonstrated the use of artificial life paradigms to optimise and improve existing simulation and simulation-related practices. For example, Seth's work explored the use of Granger Causality to detect the autonomy or emergence of a complex system (Seth, 2010), while the work by Kirshenbaum et al. demonstrated the use of simulation to educate students on Swarm Intelligence (Kirshenbaum et al., 2008). Social Modelling (11.3%) was the second most frequently utilised application domain, where social structures, networks, and situations were investigated using artificial life paradigms. The third most frequently investigated application domain is Biological Modelling (10.4%), where biological processes and phenomena were modelled and evaluated. For example, researchers modelled cancer growth using cellular automata (Monteagudo and Santos Reyes, 2013) and several primary studies modelled the phenomena of protein folding using neural networks and L-Systems (Varela and Santos, 2018).

Application Domain	Frequency
Simulation	15
Social Modelling	13
Biological Modelling	12
Robotics	9
Linguistics	7
Optimisation	6
Complex System Analysis	5
Artificial Life Modelling	5
Music Modelling	4
Disease Modelling	4
Automated Design	4
Markets	3
Ecosystem Modelling	3
Routing	2
Video Games	2
Genetics	2
Military/Tactical Modelling	2
Life History Modelling	2
Pattern Recognition and Generation	2
Other	13

Table 1: Application Domains (N=115)

Modelling & Analysis Approaches

We identified 23 unique modeling approaches in the primary study set. 57.4% of the primary studies employed *Agent-based Modelling (ABM)* as a modelling paradigm. ABM models simulate the actions and interactions of autonomous agents with the intent to assess the system-wide results of these interactions. *Cellular Automata* was the second most frequently used modelling approach with 45.2% of primary studies using it. Cellular Automata are composed of a (usually two dimensional) lattice of cells, each of which is configured to be a particular state and can affect the states

Model Type	Frequency
Agent-based Modelling	64
Cellular Automata	21
Ant Colony Systems	5
Evolutionary Algorithm	3
Neural Network	2
Robotics	2
P-Systems	2
Analytical	2
Graphs	2
Swarm Intelligence	2
Other	10

Table 2: Modelling Approaches Frequencies (N=115)

of neighbouring cells. The third most commonly utilised modelling approach was *Ant Colony* (AC), which was used employed significantly less than either of the previous two models at 4.3%. The AC model uses ant colony-inspired methods to optimise problems that can be simplified to graph representations.

The models were analysed using simulation (88.7%), analytical methods or proofs (11.3%), and once through the installation of a physical prototype (0.87%).

Artificial Life Paradigms Used

Artificial Life derives many of its paradigms from biological and social phenomena. To better understand the spread of paradigms across the papers in our primary study set, we classified the 93 identified paradigms into three main categories, namely, **Social**, **Biological**, and **Hybrid**[1]. A significant number of these (60, or 64.52%) were only identified once, and have been aggregated into the *Other* categorisation at the bottom of each Paradigm table.

Social - Paradigms that are based on social processes or phenomena, for example *Social structures*, *Artificial Societies*, and *Communication*.

Biological - Paradigms that are based on biological & physiological processes or phenomena, such as *Pheromones*, *Genetics*, and *Metabolism*.

Hybrid - Hybrid paradigms are syntheses of social and biological paradigms. This category also contains paradigms that do not neatly fit into biological or social classifications, such as *Swarm intelligence*, which has both a social and biological basis or *Pathfinding* which, while a natural process, has a clear basis in neither.

Biological Paradigms The three most commonly employed biological paradigms are Evolution, Predation, and Pheromones as shown in Table 3. Evolution was utilised as a catch-all class for paradigms that relate to modelling evolution, or utilise evolutionary computation or evolutionary concepts (such as evolutionary dynamics or morphological evolution) (Joachimczak et al., 2013). Predation refers to a predatory relationship between at least two agent classes within a complex system; one agent, the predator, consumes agents from the prey class (Seth, 2010). The pheromone paradigm relates to the use of trails left by agents in the style of biological pheromones released by ants and other creatures.

Biological Paradigm	Frequency
Evolution	39
Predation	11
Pheromones	9
Reproduction	8
Foraging	7
Artificial chemistry	4
Bacterial-based algorithms	2
Energy flow	2
Genetics	2
Metabolism	2
Morphogenesis	2
Protein Folding	2
Starvation	2
Other	21

Table 3: Biological Paradigm Frequencies

Evolution is the most commonly employed biological paradigm with 33.9% of the primary studies utilising it in some form. The frequency of *Evolution* paradigms is disproportionate when compared with all other paradigms, as the next most commonly employed paradigm across all paradigms is *Swarm Intelligence*, which was only employed in 14.8% of the primary studies, and the third most common paradigm (*Predation*) being utilised in 9.6% of the primary studies. The Other category captures a wide set of infrequently used paradigms, such as Apoptosis, Biological Growth, Exaptation and Inheritance among others. 69.57% of the primary set papers employed a biological paradigm.

Social Paradigms Social paradigms relate to phenomena that occur through agents directly interacting with each other. The most commonly employed social paradigms in the primary set are Cooperation, Semiosis, and Economic exchange as shown in Table 4. 21.74% of the primary set papers employed a social paradigm. Cooperation refers to agents helping each in order to reach a mutually beneficent outcome such as (Oswald and Schmickl, 2017). Semiosis refers to the emergence of linguistic constructs through the interaction between agents and their environment (Shibuya et al., 2018). Economic exchange refers to the exchange of resources between agents.

Hybrid Paradigms Hybrid paradigms utilise qualities from multiple other paradigm classes. For example, while Swarm

[1]Space constraints prevent us from providing the full list of papers that include a specific paradigm. We include the full tables and reference list here: `https://tinyurl.com/alife-paradigms`

Social Paradigm	Frequency
Cooperation	5
Semiosis	4
Ant colony	3
Economic exchange	3
Flocking	3
Competition	2
Crowd movement	2
Imitation	2
Social behaviours	2
Social networks	2
Other	19

Table 4: Social Paradigm Frequencies

Intelligence is a social phenomenon due to its mechanical reliance on interactions between a swarm of agents, the modelling of swarm intelligence tends to utilise biological mechanics such as pheromones for interaction.

The most frequently utilised hybrid paradigms listed in Table 5 are Swarm Intelligence, Learning, and Population Dynamics. Swarm Intelligence is the collective behaviour of a decentralised group of self-organised agents, exemplified in nature by the group activities of ants and bees (von Mammen and Jacob, 2009). Learning is a phenomena by which an agent or creature acquires knowledge about themselves or their environment through experience (Azumagakito et al., 2011). Population dynamics refers to the examination of populations in dynamical systems, with regards to how particular sub-populations are affected or affect the greater system (Bornhofen and Lattaud, 2009). 59.13% of papers used a hybrid paradigm.

Hybrid Paradigm	Frequency
Swarm Intelligence	17
Learning	11
Population Dynamics	9
Co-Evolution	5
Disease Model	3
Neural Network	2
Migration	2
Multiple Particle Interaction	2
Pathfinding	2
Stigmergy	2
Other	20

Table 5: Hybrid Paradigms Frequencies

Paradigm Frequency By Year

Figure 1 shows how often artificial life paradigms were used to model complex systems in each year of the research window. We include only paradigms with an aggregated frequency greater than four. We observe that *evolution* has been frequently employed in the past decade with a peak of use occurring in 2009. In addition, *pheromones* were used with increasing frequency until 2012.

Limitations

34.78% (40 out of 115) of the primary studies reported a form of challenge or limitation when discussing the outcome of their research. The most frequently reported limitation is related to modelling (18.96%), with paper authors citing challenges in merging Artificial Life paradigms with conventional techniques such as manufacturing methodologies with biological paradigms (Leitao, 2009; Monteagudo and Santos Reyes, 2013), challenges typical to Complex Systems such as the lack of reliability in the occurrence of emergence (Lopez, 2010), and challenges in accurately and efficiently modelling simulation environments (Azumagakito et al., 2011; Isidoro et al., 2011; Bornhofen and Lattaud, 2009). The second most frequently reported limitation is in the area of analysis (7.76% of papers), where authors referenced difficulties in the visualisation of results or models (Punithan et al., 2011), limited analytical scale (Janecek et al., 2013; Niazi, 2014), difficulty in developing analytical metrics (Taylor and Cody, 2015), and limited analysis leading to ambiguities regarding how models operate (Oswald and Schmickl, 2017). *Implementation* and *Validation* were equally reported to be challenging (4.34%). The challenges of implementation led to limitations in scalability (Krol and Popiela, 2009) and parameterisation of complex models (Yamamoto and Miorandi, 2010). The challenges of validation led to difficulties with ensuring that ensuring model behaviour is correct.

Scalability

Large-scale systems are becoming ubiquitous and as such there is a need for artificial life approaches to consider scale both in terms of the number of entities considered in the model or system, but also in terms of the number of attributes and the complexities of entity behaviours and interactions. 19 papers (16.38% of the total number of papers), evaluated the scalability of the proposed approach.

Complex Adaptive Systems Properties

22 complex adaptive systems (CAS) properties were identified in the primary study set, as shown in Table 6. Our analysis aims also to identify the artificial life paradigms that are used to facilitate specific complex systems properties, and Table 6 shows the most frequent paradigms per property. *Emergence* was the most frequently considered property with 57.39% of the papers analysing emergent properties or being designed to achieve emergence. Papers reported using 90 paradigms to generate emergence, mostly from the Biological and Hybrid paradigm categories (50 (55.56%) and 28 (31.11%), respectively). The most common paradigms for generating emergence were evolution (Otto and Bannenberg, 2010; von Mammen and Jacob, 2009), predation

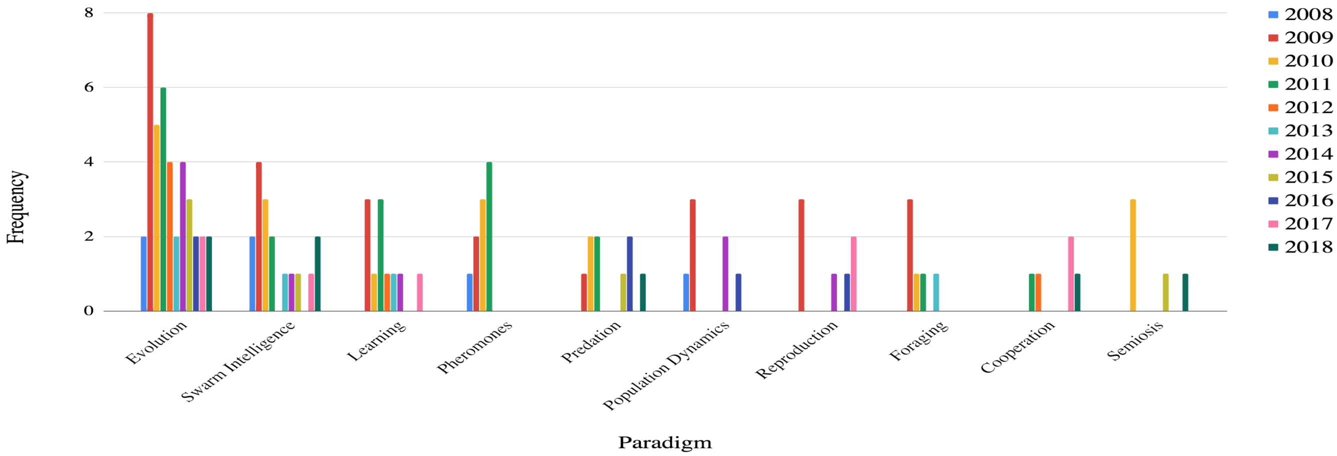

Figure 1: Paradigm Frequencies (2008 - 2018) (N = 115)

Property Name	Freq.	Common Paradigms
Emergence	66	Evolution (40.9%), Predation (13.6%), Swarm Intelligence (10.6%), Reproduction (10.6%)
Self-Organisation	33	Evolution (75.7%), Swarm Intelligence (30.3%), Predation (21.21%)
Adaptation	21	Evolution (42.8%), Learning (19%), Population Dynamics (9.5%)
Stability	4	Evolution (50%), Local Dynamics (25%), Ecosystem Modelling (25%)
Self-Regulating	2	Cooperation (50%), Pheromones (50%), Reproduction (50%)
Self-Repairing	2	Artificial Endocrine system (100%)
Self-Replicating	2	Reproduction (50%), Parsimony (50%), Evolution (50%)
Self-Evolving	2	Predation (50%), Foraging (50%), Evolution (50%)
Robustness	2	Evolution (50%), Co-Construction (50%), Metabolism (50%)
Self-Modification	1	Reproduction
Self-Configuring	1	Artificial Immune Systems, Foraging, Predation
Self-Enhancing	1	Artificial Chemistry, Morphogenesis, Pattern Formation
Autonomy	1	Flocking, Evolution, Predation
Coordination	1	Chemical Reactions, Coordination
Interaction	1	Evolution, Swarm Intelligence
Chaos	1	Velocity History, Limit Cycle
Information Storage	1	Cellular Communication
Synchronisation	1	Imitation/Memetic Behaviour
Dynamic Criticality	1	Genetics
Power-Law Distribution	1	Genetics
Stigmergy	1	Hierarchy, Pheromones, Swarm Intelligence
Plasticity	1	Co-Construction, Metabolism

Table 6: Complex Systems Properties

(Loula et al., 2010; Lopez, 2010), and swarm intelligence (Leitao, 2009; von Mammen and Jacob, 2009).

The second most frequently identified property was *self-organisation*, with 28.7% of the set identifying a systematic order arising from local interactions. It was generated using 40 paradigms, most often from the biological and hybrid paradigm classes (23 (57.5%) and 13 (32.5%), respectively). The most frequently utilised individual paradigms were evolution (Leitao, 2009; Otto and Bannenberg, 2010), swarm intelligence (von Mammen and Jacob, 2009), and choice.

The third most frequently identified CAS property was *adaptation*, present in 18.26% of papers. Adaptation was generated using 29 paradigms, mostly drawn from the biological and hybrid paradigm classes (15 (51.72%) and 10 (34.5%), respectively). The most frequently utilised individual paradigms within these classes were evolution (Bornhofen and Lattaud, 2009), learning (Fernando et al., 2009), and swarm intelligence (Leitao, 2009).

Discussion

Our data extraction identified 93 distinct artificial life paradigms, which were predominantly modelled through either agent-based modelling (ABM)(55.65%) or cellular automata (CA) (18.26%). This facilitates the simulation of complex ecological or biological models using relatively simple implementation mechanics, and account for nearly 75% of the primary studies. The remaining 25% of papers used a diverse set of modelling approaches - 18 distinct approaches in all. This demonstrates that there is still a substantial area of research that uses alternative or even modelling paradigms, but that future work is necessary to ensure that their applicability is fully understood.

While 78.26% of the primary study set identified complex systems properties, 94% of this subset identified at least one of the top three most frequently occurring properties, namely, emergence, self-organisation, and adaptation. In contrast, only 32.17% of papers considered a property outside of the top three. This narrow focus indicates a gap in research where artificial life approaches and paradigms could consider a wider range of complex adaptive system properties such as stability, autonomy, criticality, and self-regulation among others. For example, autonomy is discussed in only one primary study where the focus is on measurement and not generation (Seth, 2010). Another example is stability, which while considered in four primary studies, is often discussed without the use of any formal metrics (Punithan et al., 2011).

This limitation in existing work also translates into a limitation in evaluation, where in the majority of studies the main focus is on demonstrating that the desired emergent property occurs, without considering its potential side-effects as well as other aspects of complexity. The evaluation of existing papers is also limited through the lack of consideration for scalability, with the majority (84.35%) of the papers in the primary set not considering scalability in their analysis, thus potentially limiting the applicability of the approaches to real-life scenarios.

Complex systems are ubiquitous in a variety of domains where artificial life paradigms could be easily employed, ranging from biological or ecological modelling (Punithan et al., 2011), to project management or the design of logistical networks (Otto and Bannenberg, 2010). Our analysis identified 32 unique application domains and that 34.78% of the primary study set fell into the three most frequent application domains; *simulation* (13% of the primary study set), *social modelling* (11.3%), and *biological modelling* (10.4%). While the remaining number of application domains is fairly large, few papers were published with artificial life applications within that specific domain, with single-mention application domains representing 11.30% of the papers. This shows that artificial life paradigms are considered in a variety of application domains but that there is a need for more in-depth analysis of artificial life use within each domain to identify potential pitfalls related to their use.

Our analysis identified 93 artificial life paradigms that were employed in our primary studies, and for better discussion we grouped them into three main categories. We find that 64.52% of identified paradigms were only utilised once across the primary study set, and that 46.09% of papers utilised paradigms from one category and 44.35% of papers utilised paradigms from two categories. Similar to the discussion about complex systems properties from above, this shows that there is a clear gap in employing and validating artificial life paradigms across a variety of scenarios and application domains, and in their analysis for resulting complex systems properties. There is also a critical need for a comprehensive list of artificial life paradigms that captures the applicability of the paradigm to specific application domains in order to obtain desired properties, with sufficient modelling and implementation details to allow it to be reproduced. We consider this systematic literature review as a first step towards achieving this goal.

Conclusion

We employ a systematic literature review methodology to identify the overlap between artificial life and complex systems modeling. Our analysis identifies 93 artificial life paradigms that are used to model complex systems from a variety of application domains. Nearly 65% of the paradigms were only identified once, showing a gap in their use across a variety of domains that warrants further study. 22 complex systems properties were considered either in the design of the system, and thus facilitated by artificial life paradigms, or in the evaluation of the system, and thus potentially caused by the use of a specific artificial life paradigm. Of the papers that discussed complex systems properties, only around 30% considered properties outside the most popular set comprised of emergence, self-organisation, and adaptation, showing a need for deeper application of complex systems theory. Lastly, a significant gap has been identified with respect to scalability analysis, with only 16% of the papers considering scalability (either in terms of the number of entities or their complex behaviors and interactions) in their evaluation or design. Overall, our analysis identifies that while there is a broad application of artificial life and complex systems theories across a variety of models and domains, there is a need for more in-depth study of artificial life paradigms and complex systems properties in order to fully exploit their benefits.

References

Azumagakito, T., Suzuki, R., and Arita, T. (2011). Visualizing language evolution as an emergent phenomenon based on biological evolution and learning. *Artificial Life and Robotics*, 16(3):366–372.

Banerjee, M., Capozzoli, M., McSweeney, L., and Sinha, D. (1999). Beyond kappa: a review of interrater agreement measures. *The Canadian Journal of Statistics / La Revue Canadienne de Statistique*, 27(1):3–23.

Bedau, M. A. (2003). Artificial life: organization, adaptation and complexity from the bottom up. *Trends in cognitive sciences*, 7(11):505–512.

Birdsey, L., Szabo, C., and Teo, Y. M. (2015). Twitter knows: Understanding the emergence of topics in social networks. In *Proceedings of the Winter Simulation Conference*, pages 4009–4020.

Bornhofen, S. and Lattaud, C. (2009). Competition and evolution in virtual plant communities: a new modeling approach. *Natural Computing*, 8(2):349–385.

Bousquet, F. and Le Page, C. (2004). Multi-agent simulations and ecosystem management: a review. *Ecological modelling*, 176(3-4):313–332.

Cocco, L., Mannaro, K., Concas, G., and Marchesi, M. (2014). Simulation of the Best Ranking Algorithms for an App Store. In *Mobile Web Information Systems*, volume 8640, pages 233–247.

Davies, M. and Fleiss, J. L. (1982). Measuring agreement for multinomial data. *Biometrics*, 38(4):1047–1051.

de Buitleir, A., Russell, M., and Daly, M. (2012). Wains: A Pattern-seeking Artificial Life Species. *Artif. Life*, 18(4):399–423.

Emmeche, C. (1998). Defining life as a semiotic phenomenon. *Cybernetics & Human Knowing*, 5(1):3–17.

Fernando, S., Matsuzaki, S., and Marasinghe, A. (2009). Modeling towards homeostatic plasticity in neuronal activities. *Artificial Life and Robotics*, 14(2):262–265.

Froese, T., Virgo, N., and Izquierdo, E. (2007). Autonomy: a review and a reappraisal. In *European Conference on Artificial Life*, pages 455–464. Springer.

Holland, J. H. (2006). Studying complex adaptive systems. *Journal of Systems Science and Complexity*, 19(1):1–8.

Isidoro, C., Fachada, N., Barata, F., and Rosa, A. (2011). Agent-Based Model of Dengue Disease Transmission by Aedes aegypti Populations. In *Advances in Artificial Life. Darwin Meets von Neumann*, volume 5777, pages 345–352.

Janecek, A., Jordan, T., and de Lima-Neto, F. B. (2013). Agent-Based Social Simulation and PSO. In *Advances in Swarm Intelligence*, volume 7929, pages 63–73.

Joachimczak, M., Kowaliw, T., Doursat, R., and Wrbel, B. (2013). Evolutionary design of soft-bodied animats with decentralized control. *Artificial Life and Robotics*, 18(3-4):152–160.

Kirshenbaum, M., Palmer, D., McCullick, P., and Vaidyanathan, R. (2008). Explaining Swarm Design Concepts using an Interactive, vBottom-up Simulation Tool. In *Innovative Techniques in Instruction Technology, E-learning, E-assessment, and Education*, pages 298–303.

Kitchenham, B. (2004). Procedures for performing systematic reviews. *Keele, UK, Keele University*, 33(2004):1–26.

Krol, D. and Popiela, . (2009). Modelling Shortest Path Search Techniques by Colonies of Cooperating Agents. In *Computational Collective Intelligence. Semantic Web, Social Networks and Multiagent Systems*, volume 5796, pages 665–675.

Langton, C. G. et al. (1989). Alife i. In *Proceedings of the first international workshop of the synthesis and simulation of living systems*.

Leitao, P. (2009). Holonic Rationale and Self-organization on Design of Complex Evolvable Systems. In *Holonic and Multi-Agent Systems for Manufacturing*, volume 5696, pages 1–12.

Lopez, O. J. R. (2010). Self-organized and Evolvable Cognitive Architecture for Intelligent Agents and Multi-Agent Systems. In *Applications of Evolutionary Computation*, volume 6024, pages 392–401.

Loula, A., Gudwin, R., Ribeiro, S., and Queiroz, J. (2010). On Building Meaning: A Biologically-Inspired Experiment on Symbol-Based Communication. In *Brain Inspired Cognitive Systems 2008*, volume 657, pages 77–93.

Mittal, S. (2013). Emergence in stigmergic and complex adaptive systems: A formal discrete event systems perspective. *Cognitive Systems Research*, 21:22–39.

Monteagudo, . and Santos Reyes, J. (2013). Cancer Stem Cell Modeling Using a Cellular Automaton. In *Natural and Artificial Computation in Engineering and Medical Applications*, volume 7931, pages 21–31.

Niazi, M. A. (2014). Emergence of a Snake-Like Structure in Mobile Distributed Agents: An Exploratory Agent-Based Modeling Approach. *SCIENTIFIC WORLD JOURNAL*.

North, M. J., Collier, N. T., Ozik, J., Tatara, E. R., Macal, C. M., Bragen, M., and Sydelko, P. (2013). Complex adaptive systems modeling with repast simphony. *Complex Adaptive Systems Modeling*, 1(1):3.

Oswald, Y. and Schmickl, T. (2017). Ultimate Ecology: How a socio-economic game can evolve into a resilient ecosystem of agents. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*, pages 1–8.

Otto, S. and Bannenberg, T. (2010). Decentralized Evolutionary Agents Streamlining Logistic Network Design. In *Parallel Problem Solving from Nature, PPSN XI*, pages 240–249.

Punithan, D., Kim, D.-K., and McKay, R. (2011). Daisyworld in Two Dimensional Small-World Networks. In *Database Theory and Application, Bio-Science and Bio-Technology*, volume 258, pages 167–178.

Santé, I., García, A. M., Miranda, D., and Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning*, 96(2):108–122.

Seth, A. K. (2010). Measuring Autonomy and Emergence via Granger Causality. *Artif. Life*, 16(2):179–196.

Shibuya, N., Iizuka, H., and Yamamoto, M. (2018). Evolution of Communication Through Differentiation of Communicative and Goal-directed Behaviors. *Artif. Life Robot.*, 23(2):225–234.

Szabo, C., Teo, Y. M., and Chengleput, G. K. (2014). Understanding complex systems: Using interaction as a measure of emergence. In *Proceedings of the Winter Simulation Conference*, pages 207–218.

Taylor, C. E. and Cody, M. L. (2015). Bird song: a model complex adaptive system. *Artificial Life and Robotics*, 20(4):285–290.

Varela, D. and Santos, J. (2018). Automatically obtaining a cellular automaton scheme for modeling protein folding using the FCC model. *Natural Computing*.

von Mammen, S. and Jacob, C. (2009). Swarming for Games: Immersion in Complex Systems. In *Applications of Evolutionary Computing*, volume 5484, pages 293–302.

Yamamoto, L. and Miorandi, D. (2010). Evaluating the Robustness of Activator-Inhibitor Models for Cluster Head Computation. In *Swarm Intelligence*, volume 6234, pages 143–154.

Yu, Y.-M. and Zhao, G.-Q. (2010). Virtual battlefield and combat simulation based on Artificial Life theory. In *Proceedings 6th International Conference on Natural Computation*, volume 6, pages 2820–2825.