Unexplored Territory: Seeds For Future Research Investigations

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I. INTRODUCTION

This work outlines a number of research projects of varying scales that are interesting enough to be potentially be investigated after the completion of the present PhD research project. Project descriptions are kept brief and abstract providing a context for the investigation and an articulation of some specific areas of interest that may be pursued. Section II. summarises a series of research projects in the field of Computational Intelligence related to evolution and the application of evolutionary processes. Section III. summarises a number of general research projects not limited to Artificial Intelligence. Finally, Section IV. considers a number of less developed areas fore further research in the field of Artificial Immune Systems beyond the scope of my PhD project, as well as general interest projects.

II. EVOLUTION RESEARCH PROJECTS

This section describes a series of projects in the field of Computational Intelligence related to the application of evolutionary processes. Proposed investigatory themes include: (II. A.) morphology evolution, (II. B.) automated innovation, (II. C.) evolution of evolvability, (II. D.) evolution of collective intelligence, and (II. E.) an online adaptive system.

A. *Artificial Morphology Evolution*

In biology, morphology refers to the *form* and *structure* of organisms with little regard for the function. The evolution of morphology is concerned with the adaptive change of the form and structure of an organism over geological time. One may define morphology as the physical tools an organism uses to interact with its environment to perform specific tasks or skills. Artificial morphology evolution is concerned with the evolution of the structures of self-contained systems in the context of a problem domain. A seminal example of the application of evolutionary processes to the development of morphology directed toward simple artificial problem domains is that of Karl Sims block creatures with the objective of locomotion in various synthetic environments [36,37]. There has been much work on this problem mostly inspired by Sims involving the evolution and or coevolution of synthetic agent morphology and behaviour directed toward specific tasks.

I am interested in two aspects of this work for further investigation: (1) the formulation of structure design problems as optimisation, and (2) the simultaneous optimisation of structure and behaviour. In the first case, I am specifically interested in selecting or devising existing structure design problems and representing them as optimisation problems in an *n*-dimensional space such that search processes such as evolutionary algorithms may be applied, likely resulting in novel and or unintuitive designs to such design problems (see Section II. B.). An example of this which I have had personal experience[1] is the development of reflexive robots that must complete a synthetic terrain for the *sodarace* application [9,55]. In the latter case, I am interested in an extension of the first case that in addition to the development of

[1] Available online: http://www.ict.swin.edu.au/personal/jbrownlee/other/soda

morphology includes agents with internal control systems toward more complex behaviours. Karl Sims work is an example of this, where both the block structures of agents and the control systems that governed their actuation were evolved. An example of this of which I have had personal experience is the development of an ecosystem of adaptive agents using the open source computer game engine Quake II, where the morphology of the entire ecosystem emerged through the aggregation of discrete agent interaction and evolution [28]. An area that may provide some stimulating examples that may be abstracted is that of the evolution of body plans, and specifically insect segmentation.

B. *Automated Innovation*

Innovation refers to the application of something new, recently after its invention. Creativity refers to the ability to devise solutions to problems in novel ways. Evolution, and evolutionary algorithms have long been considered creative given their ability to develop (locate) *unintuitive* and *novel* solutions within a given problem space without or with limited bias [51]. This proceduralised and automated method for creativity has been exploited for the generation of music (evolutionary music), design (evolutionary design), art (evolutionary art), and innovation [54]. Widely cited examples of evolutionary innovation include the development of circuit design, drug design, and antenna design. Koza claims that the Genetic Programming evolutionary computation method can routinely deliver automated human competitive results [34]. He maintains a collection of examples not limited to quantum algorithms, robot control, and circuit design[2]. Goldberg claims that the Genetic Algorithm evolutionary computation method is a computational procedure for innovation where the use of a recombination of effective structures in a search space results in novel discovery [10].

I am specifically interested in the application of automated procedures such as evolutionary algorithms toward the development and application of unintuitive and novel solutions, so called '*automated lateral problem solving*'. I am particularly motivated by the potential for such methods for automated design as demonstrated in the listed example domains, and the obvious link with morphology evolution (Section II. A.). I am interested in investigating two methods for automated innovation in particular: (1) *bottom-up* method, and (2) *top-down* method. The bottom-up method involves selecting a specific problem domain and formulating a search space in which viable solutions are expected to exist. This method requires a strong understanding of the specific problem domain and is suited to those problems without existing or viable solutions. The top-down method involves selecting a problem domain with existing solutions and reverse engineering a general problem domain where existing solutions represent points or regions in the search space. Finally, the methods can be cross-referenced against each other on benchmark problem instances.

C. *Evolution of Evolvability*

In biology, evolvability refers to a given organisms ability to evolve or adapt to changes in its environment. It may refer to the plasticity of a structure or function of an organism. The evolution of evolvability refers to the adaptation of such plasticity over time. In evolutionary computation the evolution of evolvability typically refers to the selection of general search spaces in which the representation and or the operators narrow the scope of viable structures, for example the simultaneous evolution of a neutral network architecture and component configurations [20]. Another common example includes the application of a meta evolutionary process to a conventional evolutionary process and the evolution of evolutionary operators and or parameters [41]. Finally, the evolution of evolvability can be exploited in the investigation of open evolutionary systems, specifically the development of long-term incremental evolution and emergence as opposed to convergent evolutionary systems [2,4].

I am specifically interested in the investigation of the evolution of evolvability toward the development of a long-term incremental evolutionary system for problem solving. Unlike

[2] Located online: http://www.genetic-programming.com/humancompetitive.html

convergent optimising evolutionary algorithms, a adaptation-centric open evolutionary system may be developed to facilitate perpetual novelty and incremental improvement [42]. Such a system must exploit the evolution of evolvability such that adaptation is promoted and measured at multiple scales beyond simply that of solution viability.

D. *Evolution of Collective Intelligence*

Collective intelligence is the emergence of intelligent behaviour from the interaction of many lesser intelligent agents. In biology and artificial intelligence, swarm intelligence is an example of collective intelligence observed in animals. Examples include the foraging behaviour of ant colonies, the foraging and flocking behaviours of birds, and the schooling behaviour of fish. These examples of swarm intelligence have provided the basis for computational swarm intelligence, inspiring the fields of Ant Colony Optimization (ACO) [43] and Particle Swarm Optimisation (PSO) [27]. The artificial evolution of collective intelligence involves the adaptation of emergent behaviours from explicit local interactions in populations of discrete agents.

I am interested in evolving collective behaviours as a solution to specific problem domains. The formulation of problems for such a technique will likely exploit the meta-adaptation aspect from an investigation of the evolution of evolvability (Section II. C.). Adaptation will occur based on the manipulation of simplistic local behaviours such as rule sets or state machines, and the evaluation of global (emergent) behaviours in the context of the problem domain. An advanced application of this approach may involve the development of swarm intelligence strategies such as probabilistic stepwise construction from ACO, and biased particle movement from PSO, that may be exploited in the domain of computational intelligence.

E. *Online Evolutionary System*

Interactive evolutionary computation refers to evolutionary algorithms in which a human operator is involved in some way in the active process, most commonly as the subjective evaluation of evolved solutions [21]. Applications include but are not limited to art (evolutionary art) and aesthetics, computer graphics, music (evolutionary music), industrial design, speech processing, and robotic control. A commonly cited example application of the power of a human-driven selection in an evolutionary process is Richard Dawkins' *Biomorphs* in which an L-system 'creature' is evolved based on its visual expression, which is guided based on subjective human selection [56]. A more recent seminal art-based example is the *Electric Sheep* screen saver in which users may assess fractal-based animations generated on and distributed from a server that runs the evolutionary process [61].

I am interested in the application of human contribution in the assessment of solutions in an online evolutionary system, specifically a system that is distributed on the Internet. I specifically interested in the exploitation of large numbers of users contributing feedback on a problems, for which the solutions of which are difficult to assess through automated means. Human contribution may be either *directly* or *indirectly* provided to the evolutionary system. With direct contribution, users are presented with candidate solutions or portions thereof to which they directly assess. This requires explicit user participation in what is called *crowdsourcing* [32]. Two online examples of the exploitation of crowdsourcing in an interactive evolutionary algorithm are *Picbreeder*[3] and *Mutating Pictures*[4]. A potentially interesting direct-contribution application may be the exploitation of humans as innate pattern recognition machines by the identification of complex relationships through visualisation or audioisation. Indirect contribution involves the exploitation of normal user behaviour on a website or with an application that may be aggregated and provided as feedback to an evolutionary system.

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[3] Located online: http://picbreeder.org
[4] Located online: http://mutatingpictures.com

III. GENERAL RESEARCH PROJECTS

This section summarises some more general research projects that are not necessarily tied to evolutionary biology. Project areas include: (III. A.) evolution and the technological singularity, (III. B.) adaptive radiations, (III. C.) a distributed learning system, (III. D.) an applied optimisation method, and (III. E.) the development of a dynamic Computational Intelligence knowledgebase.

A. *Evolution and the Technological Singularity*

The technological singularity is the expectation that the development of Artificial Intelligence will result in a rapid acceleration of technological increase beyond which point the ability for human beings to participate and or understand. This effect and or event is termed a singularity as the existing anticipatory models of the future break down and become no longer viable [66]. Related to the singularity is the concept of Strong AI also known as Artificial General Intelligence (AGI) that describes the development of an artificial intelligence that replicates human level intelligence that may provide a path to a technological singularity.

I am interested in the role evolutionary computation may play in both a path to the technological singularity and or artificial general intelligence. Specifically I am interested in a deep investigation of the criticisms of evolutionary processes outlined by some proponents of Good Old Fashioned Artificial Intelligence (GOFAI) and the technological singularity. The first example is that of the comments by Marvin Minsky from a presentation at a game development conference in 2001 titled "*It's 2001. Where Is HAL?*"[5] in which he suggests that the problem with Genetic Algorithms is that they provide no indication of where they went wrong. Minsky's comments are rebuked by Adam Ierymenko in a blog post titled "*Marvin Minsky misunderstands genetic/evolutionary computing*"[6] where he suggests that evolution is misunderstood as a goal directed process, where in fact it is a local adaptive process. He further suggests the evolution of evolvability (see Section II. C.) as a mechanism for evolution to refine both the tools for generating viable solutions as well as the viable solutions themselves. A second example was a comment by Eliezer Yudkowsky in a presentation at a Singularity Summit in 2007 titled "*Introducing the "Singularity": Three Major Schools of Thought*"[7]. In the presentation, he suggested that evolution is too slow and or inefficient a process to develop AI or AGI (essentially brute force) and that a more efficient approach may be developed once the principles of such systems are identified. A final example is proposed by Hedrick in his discussion of the acquired immune system where he highlights evolutions lack of foresight, suggesting that features that provide a reproductive advantage are selected regardless of whether or not it is a good thing for the species [63].

This investigation may be decomposed into two separate research questions: (1) what are the limitations and disadvantages of evolutionary processes from a biological and computation perspectives, facilitating Minsky's *memory problem*, Yudkowsky's *efficiency problem*, and Hedrick's *maladaptation problem*, and (2) what role may evolutionary processes play in the development of the technological singularity and or AGI.

B. *Adaptive Radiations*

In biology and ecology, an adaptive radiation describes the rapid evolution and speciation of a single species into a variety of ecological niches. Adaptive radiations may be triggered by the colonisation of a foreign species to an isolated ecosystem, or the mass extinction in an existing ecosystem in which the radiating species is relatively unaffected. Finally, adaptive radiations may occur if a given species evolves a novel feature that makes previously unreachable niches available, such as the development of flight by birds [48]. A classical

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[5] Available online: http://technetcast.ddj.com/tnc_play_stream.html?stream_id=526
[6] Available online: http://www.greythumb.org/blog/index.php?/archives/5-Marvin-Minsky-misunderstands-geneticevolutionary-computing.html
[7] Available online: http://www.singinst.org/media/singularitysummit2007

example of an adaptive radiation is Darwin's finches of the Galapagos Islands where a common finch from South America arrived at the archipelago and radiated into at least 13 different species with specialised beaks and colours for the various environments on the different islands.

I am interested in the study of biological adaptive radiations as they may inspire similar effects in synthetic population of solutions governed by an evolutionary process. Niching is a popular technique in evolutionary computation that promotes the a speciation-like behaviour that may benefit from the integration of principles from biological adaptive radiations [29,60]. Specifically, I am interested less in the outcompeting or take-over of new ecological niches by more fit individuals, and more interested in the ability of a system to promote and maintain the radiation of a colonising species. For example, investigation may require the adoption of heterogeneous spatial schemes for assessment, such as those demonstrated successful on bacteria [49].

C. *Distributed Learning System*

The Internet is a network of network that facilitates deployment of distributed computing projects that allow large numbers of ad hoc users to contribute effort toward complex problem domains. Complex problems are decomposed into a series of work units that are consumed by clients, completed, and the results submitted back to the server. Example distributed computing projects include Folding@home[8] that focus on the folding of proteins toward curing disease and Seti@home[9] that analyses radio astronomy data in search for interesting signals [11,44]. The *Electric Sheep* (see Section II. E.) project may also be considered an example of a distributed computing project in which the execution of work units simply requires the assessment by a human user.

I am interested in the development of a distributed computing project for a learning system. The donated computer cycles would be exploited toward the improvement of the learning systems knowledgebase. Two general approaches have been considered: (1) a conventional distributed machine learning system, and (2) a learning system that requires user participation. In the first case, the system is 'conventional' in that it does not require user participation, rather CPU cycles are consumed toward the execution of machine learning algorithms, the results of which are transmitted to the server. This system may be used as a generic grid for the execution of computational intelligence experiments, or for a long-term learning process. In this latter case, concerns of continual iterative improve must be addressed such that the system does not converge (effective continued exploitation of the grid), for example see the evolution of evolvability (Section II. C.). An example of this latter case is the Terrarium Project[10] where an ecosystem extends over all clients allowing the organisms within the ecosystem to interact. For the second approach that requires user participation, the system may be an extension of the online evolutionary system (Section II. E.). Participation may involve the direct interaction with a local instance of the learning process, such as the human evaluation of solutions, or explicit tuning of the learning environment. Alternatively, and perhaps more interestingly, the user may actively define and implement modules for the local learning system that contribute to the broader knowledge base, an example of which is the user define organisms defined for Terrarium which, if successfully, proliferate throughout the distributed ecosystem.

The specific principles of interest are (1) the exploitation of large amounts of computer time directed toward continuous incremental improvement of a learning system and (2) a persistent online computational intelligence database that clients of all manner may connect and produce and consume work product for their own and the broader system's benefit. This

[8] Available online: http://folding.stanford.edu/
[9] Available online: http://setiathome.berkeley.edu/
[10] Formally located online: http://www.gotdotnet.com/Terrarium

second point highlights that the selected application should facilitate *heterogeneous clients* as well as *heterogonous computing systems*, for example autonomous work executors, domain experts that can tune local environments and contribute specialised product to the data stream, and interested non-scientists that can visualise product in their local environment and contribute in a different way to the knowledgebase. This aligns with what the IIDLE intended to provide in its initial inception [30] (also see IIDLE vision[11]).

D. *Applied Optimisation Method*

The field of data mining has a relatively structured and consistent methodology for addressing data mining problems with machine learning techniques. This method is articulated in most data mining books, for example see [24], and is sometime referred to as Knowledge Discovery in Databases (KDD) [65], another example is the CRISP-DM [64]. The method provides a best practice for clearly defining a given a problem, preparing the tools and data, application of tools, and analysis and interpretation of results. The field of computational intelligence is diverse, comprised of a variety of different techniques suitable for a variety of different problems. A specific and common problem on the field is optimisation, and there is not a consistent methodology for the application of computational intelligence techniques for addressing optimisation problems (this point has been considered by the author previously [31]).

The specific interest of this project is the investigation and development of a general method for applying computational intelligence techniques to optimisation problem domains. As was demonstrated previously, many general best practices have been Elucidated in diverse and related fields such as Mathematics, Heuristics, Operations Research, and Machine Learning, although there does not exist a clearly defined nor continuously improved methodology for applied CI optimisation. Some general concerns include although are not limited to: (1) transformations of the problem, (2) representation selection, (3) measures and metrics, (4) technique selection, (5) technique configuration, (6) visualisation, and (7) result analysis and interpretation. The research project is expected to involve much research and demonstration of specific facets of the methodology lifecycle, likely culminating in a book. The series of so-called mini projects or facets of the investigation may be captured in a series of papers, reports, essays and or blog posts, as well as a software library.

E. *Computational Intelligence Knowledgebase*

The filed of computational intelligence was formulated as a specific set of messy or soft artificial intelligence techniques a few decades ago, with some of the principle techniques such as artificial neural networks and evolutionary computation have existed for approximately 50 years. The knowledge accumulated in the field is specialised into pockets and is spread across numerous books, papers, websites, software packages, and in people's heads. Subsequently much of the work produced in the field is of little significance given the relative difficulty in assessing what is known and what the unsolved problems are. For newer researches, the contribution of the field is masked behind problem and technique detail.

I believe that a concerted and directed effort could formulate a computational intelligence knowledgebase that clearly communicates what is known, what is unknown, and what needs to be known to both raise the profile and motivate rapid advances and contribution in the field. This would predominantly be achieved through a web presence with freely available documentation and software, and would require the cooperation of numerous research leaders. The vision for CI would transform from that of small-scale experimentation in which the problem, technique, and results are typically lost, to an online knowledge capture system. All problem and algorithm instances would be defined in public software libraries with full interoperability (much like WEKA [24]), and all experimental configurations and results would be available. Given the effective definition of problems and algorithms, it will be

[11] Available online: http://www.ict.swin.edu.au/personal/jbrownlee/iidle

possible to retrospectively re-implement all seminal experiments and repeat results. Thus, rather than time spent recoding problems and algorithms and re-executing old experiments and all the problems associated with that, effort may be expended on unifying findings into coherent theories. The system would promote *standardisation* of problems, algorithms, and measures, *best practices* for experimentation, interpretation, and reuse, and multi-disciplinary participation.

IV. LESS DEVELOPED PROJECTS

This section summaries those project ideas that are less developed than those of the previous sections. These smaller subjects for further investigation are divided into (IV. A.) Artificial Immune Systems which is the subject of my PhD, and (IV. B.) General Interest.

A. *Artificial Immune Systems*

The field of Artificial Immune Systems (AIS) is concerned with the development and investigation of computational systems inspired by the structure and function of the immune system applied to information technology and engineering problem domains [40]. This section outlines some general avenues for interesting research in the field of AIS. I believe these topics will be further researched and included as '*future work*' in my dissertation.

- ***Pollination***: The relationships between the pollination of plants and the acquired immune system, specifically the cellular recognition that occurs when the gamete's meet, and the decentralised selection properties of the process for identifying suitable locations for plants of a species to grow. The relationship of pollination and distributed computing, specifically autonomic computing has been established [22,23].
- ***Self-Nonself Paradigm***: The negative selection principle and related algorithms are inspired by the acquired immune systems ability to discriminate self molecules from nonself molecules [50,62]. A particularly interesting investigation of this principle has been in the development of negative databases [16,17], and as a guiding principle in the adaptive process of information filtering [12-15]. I am specifically interested in the application of negative selection systems as an information filter and pursuing the principle in an online information management system, embodying the phrase "*I do not know what I want, but I know what I do not want*".
- ***Lymphocyte Population Biology***: Lymphocyte population biology is the study of immune cell populations using techniques from ecology and population biology. Population biology has a close relationship to clonal selection theories of antibody diversity given the theories were inspired by the field [18,46]. Some principles includes: competition as homeostasis [3,5], a continuously changing population to meet the needs of the environment [1] (and the red queen problem [39]), and the spatial distribution of pathogens [59].
- ***Cancer Evolution***: There is much in common between the evolution of some cancers and the specialisation of the acquired immune system. This relationship was identified by Burnet in the formulation of the clonal selection theory [19]. An investigation into the evolution of cancers and their ability to evade detection (anti-clonal selection) provides a complementary investigation to that of the clonal selection theory and may inspire a new field of algorithms inspired by a diverse set of somatic evolution mechanisms [8,52].
- ***Within-host Parasite Dynamics***: The intrusion of microorganisms into a host and their intra-host behaviours is referred to as within-host dynamics. The specific interest with this field is the investigation of the general principles of host penetration methods, intra-host movement strategies, and strategies for overcoming defence systems [58,67].

B. *General Research Interest*

This section lists a number of subjects for research projects related to the field of Artificial Intelligence and Computational Intelligence.

- ***Reinforcement Learning***: A machine learning field concerned with the investigation of an agent in an environment in which long term rewards are maximised is the field of Reinforcement Learning [57]. I am specifically interested in the methods for formalising delayed credit assignment and the investigation of this subject in Learning Classifier Systems (LCS) [33].
- ***Ontogenetic Learning***: Learning throughout the duration of an organisms life is referred to as ontogenetic learning as it involves adaptation without inheritable changes to the genome. Examples include the changes between the synapse of neuron cells in the brain, and the changes in the genes that are expressed in the molecular recognition in the acquired immune systems [25]. In ecology, the investigation of the effects of life-long learning and evolution is called the Baldwin effect [7,26]. I am interested in investigating the various formulations of this effect and the potential for realisation in inspired computational models. Specifically, what information is persisted and how it is maintained.
- ***Computational Biology***: The field of computational biology is the intersection of biology, computer science, mathematics, and statistics [53]. I am particularly interested in the use of statistics on large biological datasets referred to as *bioinformatics*, and the application of algorithms to automated structure discovery called *structural genomics*. I am particularly interested in the intersection of computer science, automation, and the role of computational intelligence methods (machine learning) to knowledge discovery in biology.
- ***Time***: I am interested in a basic research investigation into *time,* including but not limited to its relationship to mathematics, physics, biology, psychology, and linguistics (there are many such books, for example [38]). Specifically, I interested in a fundamental understanding of time as a concept and the perturbations of that concept that may arise with new forms of intelligence, such as those developed toward the technological singularity. Thus, the investigation may be specialised to time and the structure and function of thought and or intelligence.
- ***Data Visualisation***: The manner in which data is visualised affects the way that data may be considered. I am interested in basic research into data visualisation techniques, specifically the principles behind the application of techniques and the development of new techniques (there are many books on the subject, for example [6]).
- ***Astrobiology***: The intersection of biology and astrophysics is the field of astrobiology [35,47]. Specifically, I am interested in the definitions and limits for life, and the principles (physical, chemical, biological) of the evolution of life within planetary systems. I am also interested in the related subject of the limits of life and the study of extremophiles [45].

V. Conclusions

The general trends of the project ideas are evolution as an adaptive process, and system design and construction. Specifically many projects considered the design of systems where evolution by means of selection is applied toward the adaptation or search of structures and behaviours. Common was the clear vision that such a constructed system needs to be decentralised with suitable mechanisms to ensure the continued effective evolution, and distributed across heterogeneous computer systems, exploiting computation when and wherever it is made available.

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