Re-creating the Philosopher's Mind: Artificial Life from Artificial Intelligence

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Abstract

The ultimate goal of artificial intelligence (AI) research is to create a system with human level intelligence. Many researchers conceded that human-like interaction in a social context to be critical for human-like intelligence to emerge. Artificial life (AL) is a branch of AI to simulate the process of evolution and interaction in natural world using multi-agent systems. This suggests that AL may be a channel towards human level intelligence.

1 Introduction

The ultimate goal of AI research is to create a machine or system capable of simulating the mind in a way that can be deemed as intelligent. However, what is intelligence? More than 80 years ago, Carroll (1928) defined intelligence as "the ability to see things in their various relationships, to think complexly and coordinately in such a way as to produce a composite, or more or less unified reaction. It has its basis in neural capacity and may be defined as the coordinate functioning of related reaction groups. The degree or amount of one's intelligence is determined by his native capacity or neural complexity. It is inseparable from depth or breadth of comprehension."

In a classical book, The Physics of Immortality, Frank Tipler (1987) wondered if this world is real. Our universe may be a simulation in a supercomputer. In a similar context, modern computer games such as Diablo 3 had essentially generated a virtual world which the characters interact with each other. Is it possible to create a simulation that is intelligent by providing the critical social context for intelligence to emerge where the characters in Diablo 3 attempt to create their own AI? Or as Grand (1997) puts it, feels and considers themselves as truly alive?

However, the general focus of AI research in the last 4 decades is domain-specific problem solving (Sevilla, 2012). This approach had created complex and efficient computing systems, such as IBM's Watson, which can rival human champions in game shows. Yet, such systems are not considered as humanly intelligent but mere efficient machines. For example, a handheld calculator can perform calculations much faster than most humans today but nobody will consider a calculator as intelligent.

Many researchers had considered that human-like interaction in a social context to be critical for human-like intelligence to emerge (Rachlin, 2012; Schweizer, 2012). This suggest that intelligence is a grown attribute, rather than by design. It had been argued that the architecture of intelligence may be difficult to define (Chik and Dundas, 2011), which is crucial for a top-down approach. As a result, a new trend of AI research employing multi-agent systems, such as ant colony optimization (ACO) (Dorigo and Di Caro, 1999), that allows intelligence to be grown, and adaptive learning algorithms such as IBSEAD (Dundas and Chik, 2010), had emerged. If human interactions are needed for human intelligence, then perhaps ACO is able to evolve ant intelligence.

This manuscript argues that Artificial Life (AL) can provide the social context for intelligence to emerge. Another area where the term "artificial life" is used is in synthetic biology with aim to create biological life-forms (Baertschi, 2012), which is generally called "wet artificial life".

2 What is (Soft) Artificial Life?

Using concepts of cellular automata, Langton (1986) showed that agents behaved in a life-like manner in a virtual reality world employing fundamentally life-less chemical concepts. This area of research came to be known as Artificial life (AL), which is a branch of AI that intersects with biology, ecology and simulation, to examine life "as it could be" (Moreno, 2002; Rasmussen et al., 2001). It is based on the creator-style approach (Chik and Dundas, 2011) using multi-agents to simulate the process of life and had been suggested to be able to insights into phenomenon in everyday world (Froese & Gallaghe, 2010). In this virtual world, the agents interact with a defined set of artificial chemistries (Dittrich et al., 2001) to keep themselves alive. To some extent, AL is the ultimate "playing god" where a world/universe is created to test a hypothesis.

In another point of view, AL is a virtual replay of the evolutionary tape. Stephen Gould (1989) had argued that the outcome of life, both general and in detail will be very different from what we have today should evolution be repeated again. This concept had been used in many AL research to examine the process of evolution, biological (Harvey, 2011; Jones, 2011) and informational (Kim and Cho, 2006). For example, Fontana (2010) had demonstrated that propagation of ALife organisms (digital organisms; DOs) can simulate cancer formation, while Ward et al. (2011) used ALife to model movement of pathogens.

To facilitate ALife research, many simulators had been developed (Bornhofen and Lattard, 2006; Komosinski and Adamatzky, 2009). Common ALife simulators include Tierra (Ray, 1992), Echo (Holland, 1992), Polyworld (Yaeger, 1994), Framesticks (Komosinski, and Ulatowski, 1999), Avida (Ofria and Wilke, 2004), and EcoSim (Gras et al., 2009). These platforms had helped research explore various aspects of natural evolution such as the effects of mutation rates (Nelson and Sanford, 2011), pathway duplication (Gerlee et al., 2009), evolution of physical morphologies (Komosinski and Rotaru-Varga, 2001) and the role of physical barriers in driving speciation (Golestani et al., 2012).

The theory of evolution proposed that the first living cell arose rather spontaneously out of the inert chemicals at around 4 billion years ago. Hence, human intelligence is a product of evolution over these 4 billion years. The first living cell may only have properties such as the ability to use external chemicals for energy, and the ability to replicate itself. These properties had been observed in AL, though in an artificial chemical context (Dittrich et al., 2001). In addition, Thompson (1997) argued for AL to be the basis for AI by formalizing and interpreting the symbolic data in the context a dynamic system, and used the analogy of DNA (symbolic) to amino acid (interpretation) translation. This suggests that AL may be a useful experimental tool to examine how interactions and evolutionary process may give rise to a repertoire of intelligences, including human intelligence, over extended periods of simulation.

3 Artificial Life to Artificial Intelligence

Steels (1993) presented AL approach to AI as "bottom-up AI" and "behavioral-based AI" which should be considered as living and also implied that separate agents or organisms working may generate new behavior, which is known as emergent behavior. A survey from AL community also agrees that bottom-up approach is a significant accomplishment by AL research (Rasmussen et al., 2001). However, there had been little research over the last 2 decades to grow AI out of AL compared to the number of studies done on AI and AL independently. A cursory search using title words in Google Scholar showed about 6500 and 960 hits using "artificial intelligence" and "artificial life" respectively, but only about 30 hits when both terms were used.

The major advantages of evolutionary approach compared other learning approaches is eliminating the need for complex problem formulation, yet capable of generating optimal solutions (Hubley et al., 2003). Downing (2004) defined six characteristics of emergent behavior. At the basis, duplication needs to occur. Behavioral features or characteristics are repeated in subsequent generations. However, this results in consistency which ensured that no emergent behavior can occur over time. Hence, differentiation needs to occur to introduce minor differences over time. This will allow for new or variant characteristics to emerge over time. Both original and emergent behaviors have to move out of their original position to form cliques of similar behaviors. This will require migration and extension. As cliques are formed, they may reinforce their behavior via the act of cooperation or compete against each other. The goal is to evolve populations of DOs with both high level of cooperation within the population and high level of competition between populations. This is similar to that observed in human brains based on functional imaging (Chaminade et al., 2011; Decety et al., 2004) Thus, Downing (2004) proposes to start populations of DOs with the six primary characteristics and allow them to evolve independently and together as a whole using cooperation and competition as fitness measures.

Cooperation and competition are fundamental characteristics of social behavior. For example, at a micro-scale, human brain is a composition of specialized modules cooperating and influencing each other. On a macro-scale, our economy is a collection of cooperative and competing entities, such as various consumer groups and supply chain. Hence, if populations of cooperating and competing DOs represents a fundamental neuronal model of activity, it may be possible to study social behavior using DOs. A review by Mitri et al. (2012) had shown that simulated robots, which are synonymous with DOs, were useful tools to study social behavior. In Guns, Germs, and Steel, Jared Diamond (1998) argued that a critical mass of individuals is needed for innovation and specialized behavior to occur. This implied parallels between neuronal activity and social behavior, grounded in the characteristics of emergent behavior. This suggests that stigmergistic (indirect coordination) interactions of different entities in a system can result in a complex adaptive system (Mittal, 2012), which is characteristic of intelligence or cognition (Doyle and Marsh, 2012). Gabora and DiPaola (2012) had used artificial neural networks and genetic algorithms in DOs to demonstrate that chaining previously emergent techniques in generative art is capable of producing human-perceived creative art works. However, it cannot be assumed that social behavior uni-directionally influenced the entities as Galkin (2011) had argued that DOs might model social dynamics, suggesting that the interaction and influence of organisms and its social environment is bi-directional. In addition, a concept known as "social brain hypothesis" that suggest a correlation between animal brain size and social complexity had been supported by a number of animals, including humans (Powell et al., 2010), monkeys (Charvet and Finley, 2012), dogs (Finarelli and Flynn, 2009), hyena (Sakai et al., 2011), and fish (Gonzales-Voyer et al., 2009). This suggests the importance of social interactions in the emergence of intelligence, which is supported by archaeological records a correlation between emergence of human intelligence and creativity and increase social abilities (Gabora and DiPaola, 2012). Therefore, it seems plausible that a critical density of cooperating and competing DOs may be an avenue towards intelligence.

With this concept, how can we implement a truly intelligent and creative machine using DOs? It seems that DOs can be implemented at two levels – intra-organism and inter-organism. At the intra-organism level, DOs can represent neuronal cells that make up a brain, which is made up of different specialized functional modules (Caramazza and Coltheart, 2006). Populations of DOs can representative each of these functional modules. At the first stage, these populations can be homogeneous and un-specialized but implemented with the six characteristics of emergent behavior as suggested by Downing (2004). These can be left to simulate to create specialized modules based on cooperation and competition. There is a need to prevent over-specialization of these modules as specialization is inversely proportional to the ability to adapt to future changes. Hence, some degree of variability is needed for future adaptation. However, Zufall and Rausher (2004) suggested that portions of un-utilized genome may be a buffer to accumulate mutations for future evolutions into new functions. This suggests that a means to ensure ability to adapt to future changes may lie in maintaining a sub-maximal utilization of the genome. Once this is accomplished, it may be considered as a primitive brain which can then be "encased" into a second layer of DOs, which represents individual organisms. At this second stage, the first "encased" DO can be considered as a proto-human, which can be cloned to give a critical density. Social behavior can be added to simulate interactions between proto-humans to evolve into intelligent beings.

4 Concluding Remarks

Kaess (2011) had argued that AI is unlikely to produce human-like consciousness but Sevilla (2012) argued that AI may be a road towards creating artificial wisdom. It is not possible to tell what intelligence, wisdom or consciousness we may eventually create in this path of research. However, it will be interesting to see where replaying our evolutionary tape may bring us this time. Nevertheless, I believe it will be an interesting day when our computers feel "human" (Schlinger, 2012) or when our simulated humans (the characters in a future version of Diablo) start to create their own artificial intelligence.

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