Evaluating the current applications of Swarm Intelligence with regard to domestic usage.

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Contents

Abstract

Ants are extremely simple animals, if left alone most would struggle to survive. However a colony of ants is capable of achieving incredible feats such as finding the shortest route to food sources and keeping the nest temperature constant to within a degree. It is not just ants that work together for mutual benefit; many birds, fish and other animals flock together as a defense against predators. The study of this phenomenon and of systems sharing these properties is known as Swarm Intelligence.

The purpose of this dissertation is to investigate Swarm Intelligence (SI), paying particular attention to its current and future applications. To inform this goal, a description of Swarm Intelligence has been established, situating it within the larger field of Artificial Intelligence. Following this, it was necessary to analyze the useful methods and principles that can be extracted from natural swarms. It is then demonstrated how these underlying principles have been developed into two optimization algorithms; Ant Colony Optimization and Particle Swarm Optimization, which are utilized in a number of real-world applications. It was also important to look at the field of Swarm Robotics, which applies similar swarm principles to the field of robotics, allowing the swarm model to be realized in hardware as well as software.

Using case studies of current swarm applications not only indicates the current state of this technology, but also provide a useful source of inspiration for discussing the implementation of a swarm model in different environments, specifically domestic. These findings made it evident that a swarm-based hardware application in a domestic environment has had considerably less discussion and speculation than, for example, a military environment. My concluding argument is that a domestic environment could potentially benefit from a swarm-based hardware application, and it is not unreasonable to initiate discussion thereof.

Introduction

> *Put a hundred army ants on a flat surface and they will walk around in never decreasing circles until they die from exhaustion. But a colony of a million army ants is a sophisticated "super-organism." The colony carries out its legendary raids and can even keep nest temperatures constant to within a degree. An army ant colony seems endowed with an intelligence far beyond that of any individual ant (Franks, 1989, p.138).*

A colony of army ants is a fascinating example of collaboration in the natural world, as documented by N. R. Franks. We know that individual ants are behaviorally simple insects with limited memory, however collectively these ants manage to perform many complicated tasks with a high degree of consistency *(White, 1999)*. Army ants are just one example of many that provide a wealth of inspiration to the field of Swarm Intelligence.

The goal of this dissertation is to investigate Swarm Intelligence (SI), paying particular attention to its current and future applications. Out of these applications, this paper will focus specifically on domestic technology, and as well as analyzing current trends, will assess how suitable the swarm paradigm would be to potential applications in this field.

To begin constructing an informed response to the title of this dissertation, this paper must be broken down into a number of parts. Firstly it is important to define the concept of intelligence, and establish a working vocabulary for the duration of this thesis. To help contextualize Swarm Intelligence it is necessary to give an overview of human, animal and artificial intelligence (AI), highlighting key debates and influential theories. A specific debate in the field of Artificial Intelligence is the Strong vs. Weak AI debate, which will be covered and its consequence noted. Following this, a wholesome description of Swarm Intelligence is required, which will also situate it within the larger field of Artificial Intelligence. It is also desirable at this point to note the methodologies and analytical viewpoints from which swarm intelligence is generally approached.

The next step in accomplishing the goal of this thesis is to make a detailed analysis of what uses and methods we can extract from the swarm model. This involves expanding on the two successful algorithms that have emerged from swarm research; Ant Colony Optimization and Particle Swarm Optimization. Without going into unnecessary technical depth of the algorithms, a general explanation of how they work must be established. It should also be determined what class of problem they are best suited to, and what degree of success they have encountered. This chapter also looks at how the relatively young field of *swarm robotics* uses the principles of Swarm Intelligence and applies them to numbers of autonomous robots. Looking at the motivations for swarm robotics, and using a case study of the Swarm-bots project, helps determine what strengths and weaknesses the swarm model hold over existing centralized robotic systems. From this is it possible to determine what domains of application the swarm algorithms and swarm robotic systems might be best suited to.

Having determined the main advantages of the swarm model and the type of problems that it best suits, a wise next step would be to expand on some examples of real-world applications of the swarm paradigm. Doing this offers a good indication of the current state of this technology, allowing more accurate predictions to be made about the future. It also provides a useful source of inspiration for discussing the use of this technology in a different context, specifically domestic. By breaking down the current applications into two sections; Software & Simulation, and Hardware, it is possible to give an accurate and unbiased overview of the saturation of Swarm Intelligence across all domains. By using these case studies, we are better qualified to initiate discussion and formulate some predictions about the possible domestic applications of Swarm Intelligence.

Human, animal and artificial intelligence

To inform the goal of this thesis and to help contextualize Swarm Intelligence it is important to give an overview of human, animal and artificial intelligence. Particular attention will be paid to the key debates in each field, especially those surrounding artificial intelligence research. Before doing this, it is important to distinguish between the concept of mind and intelligence, and then provide an adequate definition of 'intelligence' to establish a working vocabulary for the duration of this paper.

Distinguishing between mind and intelligence

There are contrasting views amongst philosophers on what exactly the mind consists of, and whether it is connected to the body. Many modern philosophers adopt a physicalist or materialist position, meaning that the mind is part of the body, and is a physical object in all senses *(Stoljar, 2005)*. The dualist or antimaterialist view however, is that the mind is not a "substance" or physical entity that we can interact with, it is a group of independent properties that emerge. Most non-philosophers hold this view, and it is probably the oldest and most widespread theory of the mind[1] *(Graham, 1999, p.295).* Pascual F. Martinez-Freire of the University of Malaga *(1998)* takes on this antimaterialist view, and makes some useful hypotheses based on the criteria of folk psychology. He believes that the mind is made up of a collection of "mental processes" that can be empirically studied.

> *Using concepts taken from the information theory we can distinguish, in the beginning, four main types of mental processes: 1) perceptions, i. e. organized reception of information, 2) memories or storage of information, 3) beliefs, that is, judgements about the received information, and 4) plans, namely, arrangements of information to act. (Martinez-Freire, 1998)*

To put this into a more accessible description, we have sensations and perceptions from our own and external bodies, which allow us to mentally

[1] More information on the philosophy of mind can be found in the book: Philosophy of Mind by George Graham.

construct a definite object. We retain memories from several sources, whilst at the same time elaborating them with varying degrees of creativity. We form beliefs about ourselves and other people, things and ideas, whilst also being able to make plans to solve problems or purposes based on perceptions, memories and power of reasoning *(Martinez-Freire, 1998).*

Martinez-Freire states that there are three kinds of mind: human, animal and mechanical, however the best example of mind has arisen from the carbon-based substrate of human anatomy. Because of this we take the human mind as the paradigm or model of mind to study other minds. To explore the idea of mind in animals, analogies must be drawn with human mental processes, for example if an animal is observed showing reception of information, then we can attribute some type of sensation or perception to it. Intelligence, however, is not a direct product of the mind. The antimaterialist approach to looking at intelligence is that each of the (mental) processes that make up the mind has the potential to be intelligent, however not all are intelligent. Many interpretations of the word intelligence exist, and in order to unpack these key areas further, it is important to define intelligence.

Defining Intelligence

It is very difficult to find a definition of intelligence that satisfies both computer scientists and psychologists, and has been a notable debate since research in this area began. Martinez-Freire summarizes the extent to which different doctrines of science regard intelligence in his 1998 paper Mind, Intelligence and Spirit:

> *It is very common among psychologists to defend that the intelligence is not an abstract faculty. On one side the intelligence is not an individual thing, but a class of processes […] On the other side, intelligent processes are relative to different contexts, in such a way that we can say that a general intelligence does not exist. Intelligent processes should be understood by specifying a domain of application. For example, we can not compare the intelligence of a computer to prove theorems and the intelligence of a beaver to construct a lodge (Martinez-Freire, 1998).*

Different characterizations have been offered by psychologists to try and define intelligence, such as ability to learn, problem solving ability and power of reasoning. The strongest of these candidates being problem solving capacity, as it could be said all intelligent processes require the ability to solve problems, and so inherently problem solving is a criterion of intelligence. Michael Hand *(2007)* outlines that there should be a basic distinction made between the ordinary and technical sense of the word intelligence. He describes ordinary as being the widely adopted meaning understood by English speakers used in everyday context, e.g. the chess player made and intelligent move. The technical sense is a deliberate deviation from the ordinary sense introduced to serve particular theoretical purposes, however is still remarkably unspecific to one meaning. Hand also concludes, despite finding fault in many previous definitions of the word, that intelligent process is something understood by specifying a domain of application, backing up Martinez-Freire's earlier claim[2].

For want of a "consensus" definition that provides a clear description for the more general use of the word intelligence, we look to the article "Mainstream Science on Intelligence" which was signed by 52 intelligence researchers in 1994:

> *A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—"catching on", "making sense" of things, or "figuring out" what to do (Gottfredson, 1997, p.1).*

From these sources, it is possible to extract two definitions of intelligence; firstly a more general usage of the term describing a broad capability for comprehending our surroundings and "making sense" of things. Secondly, we can assume it also represents problem solving ability in a particular domain of application, as suggested by Martinez-Freire and Hand. It is also possible to

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[2] A complete introduction to intelligence can be found in the book; Intelligence: A Very Short Introduction by Ian J. Deary.

adopt the belief that not just humans have minds; animals are also thought to have minds and are capable of exhibiting some degree of intelligence in specific domains. Given the goal of the dissertation, a wise next step would be to examine some key areas of animal intelligence.

Animal Intelligence

The prevailing view on animal intelligence dating back to Descartes is that non-human primates cannot think because they cannot use language. When I say language, I refer to the expressive kind only used by human beings that proves practically limitless in its ability to embed meaning and encode information *(Dennet, 1994)*. It is commonly known that other forms of language exist in the animal domain, such as body language and rudimentary communication in birds, insects and mammals, however the difference in complexity of human symbolic language is enormous. It is thought that conscience, thought, planning and many other higher cognitive functions in humans are determined by this capacity for symbolic representation.

The views of B.F. Skinner, a notable behaviorist who supported Descartes ideal, held the view that all examples of animal intelligence were simply conditioned behavior that didn't require cognitive explanations. Recent research has challenged these old-fashioned views and provides sufficient evidence to prove that animals (specifically non-human primates) can think without language *(Brannon, 1998, p.746)*. Experiments where undertook that prove that two male rhesus monkeys can correctly order a number of different objects on a screen without the help from external cues, showing that without recognizing any symbols or understanding of language they have the capacity to master simple arithmetic, on-level with that of a two-year-old child. Brannon and Terrace believe that language skills evolved after arithmetic skills, providing a possible glimpse of how humans evolved from our primate cousins. This interesting revelation solidifies the trend in understanding of intelligence from within the field of Artificial Intelligence. Before the 1990's it was believed that intelligence could be simplified and understood merely by symbolic representation, however this research goes some way to proving that certainly in the case of animal intelligence, a deeper understanding requires a sub-symbolic approach.

Beside from non-human primates, many animals show intelligent mental processes in different domains, e.g. pigeons excel at visual discriminations and can distinguish between male and female faces, and among paintings by different artists. They can also group pictures into categories such as trees, selecting those belonging to a category by pecking with their beaks. *(Dicke, 2008)* Bees are exceptionally good at mapping the location of pollen sources and conveying this information to other bees in the hive, using the 'waggle dance' first identified by Von Frisch. *(Dewey, 2008)*. Some animals also display human-like social behavior, for example dolphins have been shown to care for an injured pod member, displaying the fairly sophisticated emotion of empathy. These social behaviors should not be confused with the considerably greater 'general intelligence' of human consciousness, as later described.[3]

Russell A. Dewey, PhD of University of Michigan *(2008)* speculates that animal awareness must be more "immediate and reactive" than humans, dependant upon immediate stimulation. This opposes the human ability of being able to grasp and manipulate thoughts, considering possible outcomes and applying reasoning to achieve the best choice of action.

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[3] A common misconception when discussing animal intelligence is that because animals sometimes display emotions, intentions, plans and reactions (things we associate with human consciousness), that they have the same consciousness as us. According to Russell A. Dewey, PhD of University of Michigan they may possess a non-linguistic consciousness; however it is nothing near the reflective self-consciousness or "characteristic inner chatter" of humans that likely holds the key to humans' superior intellect. Dewey provides a playful example of how humans might glimpse the possible language-less conscious of a non-human animal:

> *"Probably the closest we get to the consciousness of an alinguistic creature (i.e. a non-human animal) is in the moment after awakening to an alarm clock when our brain is not yet fully functioning. We nevertheless see our environment and react well enough to get out of bed, perform basic body functions, and start our day. But for that moment we may experience consciousness without the characteristic inner chatter of humans. During that time our consciousness is very direct and sensory-oriented, and we may greet a friendly dog or cat more or less as alinguistic equals." (Dewey, 2008)*

It can be safely said that although research favors the idea that intelligence can manifest in an animal without the understanding or grasp of language, it's the usage and comprehension of these symbols that accounts for the large distance between intelligence in animals and humans[4]. It is believed that animal awareness and thought processes are more "immediate and reactive" than humans, and responsive to stimulation in their environment.

Human Intelligence

It is important to briefly look at human intelligence, highlighting the main differences between human and animal intelligence, also noting what possible contributors this could be caused by.

> *Language is the most defining feature of human intelligence: without syntax -- the orderly arrangement of verbal ideas -- we would be little more clever than a chimpanzee (Calvin, 1998).*

William H. Calvin *(1998)* argues that human's grasp of language is responsible for a number of other outstanding features of human intelligence, namely the ability to plan ahead. He argues that this ability is surprisingly un-evident in animals, besides from hormonally triggered preparations for winter. These planning abilities stem from borrowing mental structures for syntax to judge combinations of possible actions. We do this by making narratives of what might happen next, and applying syntax-like rules of combination to rate a scenario as unlikely, possible or likely. Isolating the physical part of the human mind that is accountable for the grasp of language has been a problem facing researchers for years, due to human brains being anatomically very similar to that of other primates. Dr Simon Fisher from the University of Oxford believes that the ability to speak is encoded in our genes inherited from our parents, specifically a gene known as FOXP2. *(Fisher, 2005, p.111)*

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[4] Whether or not the consciousness of any animals involves self-awareness is another issue that is still unknown. The psychologist Gordon G. Gallup conducted research into self-recognition through experiments involving apes looking into mirrors. *(Gallup, 1970, p. 86)* Although Gallup proved that apes could recognize their own images in a mirror, the research was inconclusive and could not prove that the apes where self-aware.

This provides a clue as to what contributes to human's heightened 'general intelligence' as opposed to animals. As noted previously, it is useful to take the human mind as the paradigm of mind to study, and the field of Artificial Intelligence makes studying it one of it's primary goals, as will now be discussed.

Artificial Intelligence

Artificial Intelligence (AI) is a subfield of computer science, and is concerned with understanding the nature of intelligence and constructing digital systems capable of intelligent action. Its purpose can be broken down to the following; firstly to further scientific knowledge of natural intelligent systems and secondly to advance computer sophistication in the service of humanity *(Schwartz, 2002).* There is no single unified theory that directs AI research, resulting in a huge variety of subfields, from general-purpose areas such as perception and logical reasoning, to specific tasks such as playing chess, proving mathematical theorems, writing poetry, and diagnosing diseases. It is common for scientists in other fields to gradually move into artificial intelligence, as it can provide the tools and vocabulary to assist in a variety of ways *(Russell, 1995)*. This fragmentation of the field means that different institutions try and tackle specific problems, and develop particular tools to help solve them *(Mccorduck, 2004)*. There have been a number of notable approaches to solving AI, early attempts can be categorized as "good old fashioned AI" and assumed that intelligence can be reduced to using high-level symbols such as words or ideas (Symbolic). Since the 1980's Sub-Symbolic AI has gained precedence over the former, as the limitations of symbolic AI where reached. More recent advancements in AI have come from the Statistical AI approach, which integrates a number of different approaches based on mathematical tools, which are scientific by nature and the results verifiable. The goal of these tools that are developed is to solve problems in computer science, and inform the field of AI as a whole.[5]

[5] An introduction to Artificial Intelligence can be found in the the book; Artificial Intelligence: A Modern Approach by Stuart Russell.

The Key Debate

Due to the complex nature of the human mind, in which AI attempts to help understand and replicate in some form, many philosophical questions and debates about AI exist. It is obvious from the title of AI, that the ambiguous nature of intelligence and the debates surrounding that are persistent to this field also. However the overall goals of AI also raise heated discussion, and there has been a large divide for many years over what the field intentions are, this can be put in the form of a question; “Strong” versus “Weak” AI.

Strong AI makes the claim that human intelligence (mental processes) can be broken down into formulas and mathematical equations, therefore making it possible to one day be reproduced by a machine. In other words, giving birth to a completely artificial mind. Sloman, a notable contributer to this field presents a scale of strong–to–weak AI, utilizing what he calls Undiscovered Algorithms of Intelligence (UAI) to represent levels of ambition.

Weak AI claims that computers are a useful tool for studying intelligence and developing useful technology. However unless they are constructed significantly different from today’s technology, can only at best be a simulation of a cognitive process, and not itself a cognitive process or in any way considered to be a mind. This viewpoint was established by John Searle, and formed the basis for his famous “Chinese Room” argument. This made an important point that just because a system functioned with expected outcomes, it doesn’t necessarily mean that the workings of the system can be fully understood by the system *(Gams, 1997; Cole, 2008)*.[6]

The Weak AI viewpoint offers a considerable lower ambition than Strong AI, and many scientists believe that human intelligence and consciousness is not well enough understood to be re-created using current AI approaches. Suydam eloquently summarizes why he believes Strong AI can never be accomplished.

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[6] More details on Searle’s Chinese Room argument can be found on the Stanford Encyclopedia of Philosophy; http://plato.stanford.edu/entries/chinese-room/

> *AI researchers have dared to believe that they can understand intelligence well enough to literally describe how it works. By turning this description into a set of instructions a computer can follow, the computer becomes intelligent. […] But designed intelligence is bound to underwhelm, for the simple reason that to design is to cheat. When we design an AI, it exhibits our intelligence and pursues our goals. In other words, the intelligence and motivation is external to the entity that acts on it. In contrast, true intelligence emerges intrinsically, of its own accord. It is self-motivating, because it determines its own goals (Suydam, 2008).*

It is believed that there are many characteristics of human intelligence that cannot yet be re-produced by a machine. Despite this, a number of relatively successful artificial simulations using a similar model to the brain's neural network have achieved learning capabilities and other human-like characteristics of intelligence in a small number of areas.

Alan Turing, a notable theorist in AI research claimed that; "If a machine acts as intelligently as a human being, then it is as intelligent as a human being." Suggesting that, ultimately, we can only judge the intelligence of machine based on its actions and behavior. Turing had been exploring "machine intelligence" since the 1940's and devised a test known as the Turing Test, which could provide a hypothetical and theoretical method to demonstrate the intelligence of a machine. The test involved one human judge, who engages in a natural language conversation with one human and one machine using a text-only medium such as a computer keyboard and screen. All three participants are in separate locations, and if the human judge cannot reliably tell the human from machine then the machine is said to have passed the test. In order to pass the test the computer program would have to posses the following capabilities: natural language processing, knowledge representation, automated reasoning and machine learning. Whether or not the computer is truly intelligence if it passes the test is still debatable, however the test provided a marker, which allow progression to occur without constantly being held back by the question *(Turing, 1950)*.

Summary

Early in this chapter it was established that the word intelligence really has two different meanings, a general intelligence that involves a number of different problem solving abilities that lead to “making sense” of our environment, and secondly a problem solving ability in a specific domain of application. A brief overview of animal intelligence proved that despite lacking the multitude of cognitive abilities thought to make up human intelligence, animals often excel at tasks in a given domain of application. It is thought that animal mental processes are more “immediate” and “reactive” of their current environment, opposing human’s ability to plan ahead and predict possible outcomes of their actions.

The motivations of artificial intelligence are to further our understanding in biological intelligence, and to create intelligent entities. Whether AI can ever achieve true intelligence or produce an artificial “mind” is a key debate that like many philosophical questions has no correct answer. Neither animals nor computers are thought to share the ‘general intelligence’ or vast display of cognitive processes possessed by the human mind. However, they are both able to demonstrate a certain level of intelligence when specifying domains of application. One of the areas in which the study of animal behavior has directly inspired and influenced AI research is Swarm Intelligence, which will now be described in greater detail.

What is Swarm Intelligence?

Having identified that most animals individually lack any planning ability and many other 'higher' cognitive processes that the human mind posses, how is it then that we see examples in nature of incredible collaboration and complex tasks being achieved by colonies of ants? It is not just ants that work together for the benefit of the swarm, many birds, fish and other animals flock together as a defense against predators *(Miller, 2007)*. The study of this phenomenon and development of systems based on this swarming model is called Swarm Intelligence, and it sits within the larger field of Artificial Intelligence.

Swarm intelligence in nature

Swarm behavior in nature is broken into two categories; voluntary and involuntary. Voluntary animals swarm because they can benefit in some way, the best example of this is the aerial ballet performed by a flock of birds, flying synchronously together, swiftly and collectively responding to their environment and needs. It is suggested that there are a number of benefits achieved by flying in a flock, firstly they are far less likely to be attacked by predators, as is proven by Kenward *(1978).* There is also a higher chance of locating food when the sources are unpredictably distributed in patches, and they decrease energy usage on long flights when adopting a tight formation *(Wilson, 1975)*[7]. Reynolds and Heppner are two notable scientists that where intrigued by birds' ability to flock synchronously, often changing direction suddenly, scattering and regrouping, etc. Both of which had the insight to suggest that basic local processes and awareness within each bird might underlie the unpredictable group dynamics of bird social behavior *(Kennedy, 1995)*. Reynolds identified three local processes that where required to re-create the flocking behavior in birds; **separation** – steering to avoid crowding flock mates, **alignment** – steer towards the average heading of local flock mates and **cohesion** – steer to move toward the average position of local flock mates *(Reynolds 1987)*. It should be

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[7] More examples of natural swarms can be found at the National Geographic article "The Genius of Swarms" by Peter Miller, available at: http://ngm.nationalgeographic.com/2007/07/swarms/miller-text/1

noted that “local flock mates” represents only objects in a certain neighborhood, based on the perception of the individual *(Pfeil, 2006)*.

Involuntary swarms usually consist of social insects whose members cannot survive on their own and can often achieve a number of impressive tasks to a high degree of accuracy, despite the relative simplicity of the individual. A prime example of one of these tasks is an ant colony foraging for food, which as detailed in the next chapter has inspired a very efficient optimization algorithm. Individual ants deposit a chemical substance called a pheromone as they move from a food source to the nest, this pheromone is then followed by other foraging ants. After a period of time, this ultimately results in the optimum (shortest) route to the food source being used by the majority of ants. Figure 1 illustrates an experiment of how a colony of ants discovered the shortest path the food source.

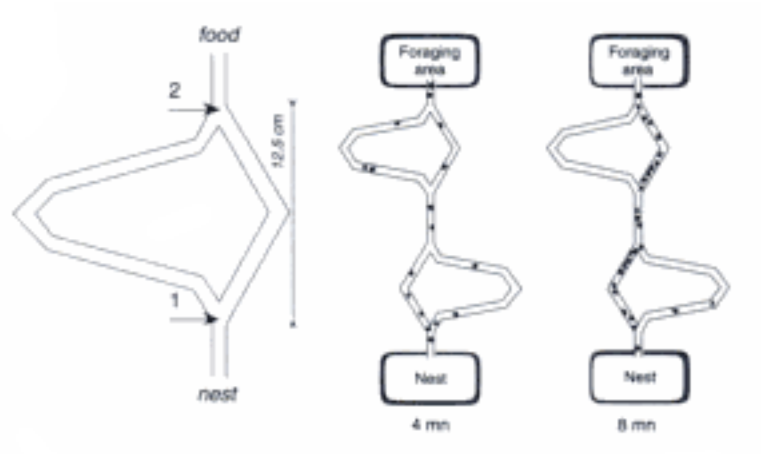

Figure 1. Colony of ants (Linepithema humile) after 4 and 8 minutes after a bridge was placed between nest and food (Goss et al., 1989).

The organization of involuntary swarms is not achieved by a central control, rather a process known as stigmergy. Stigmergy involves indirect communication by leaving markers in the environment, stimulating other individuals to behave in a certain way *(Bonabeau, 1999)*.[8] It is this de-centralized co-ordination that allows ant colonies to be so robust, meaning that if one

[8] An introduction to stigmergy can be found by Eric Bonabeau in the journal article; Editor’s introduction: stigmergy, in *Artificial Life,* volume 5, issue 2 (April 1999).

individual dies, another can easily replace it's duties, and the overall system is not affected.

Defining swarm intelligence

Bonabeau, Dorigo and Theraulazn *(1999)* describe Swarm Intelligence as "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies". Meaning that everything we artificially create that is inspired by natural swarms is Swarm Intelligence. The terminologies used to describe similar concepts within this area of interest are often confused, so it is important to clarify them now. Examples of naturally occurring swarm behavior is often referred to as 'swarm intelligence', however the field of Swarm Intelligence (SI) is the study of these natural swarm behavior with the intent on informing Artificial Intelligence research and creating artificial systems.

Where does Swarm Intelligence lie in the rest of Artificial Intelligence?

Swarm Intelligence is classified as a form of Evolutionary computation, which is itself a Search & optimization type of tool used to inform Artificial Intelligence. It is regarded as a bottom-up approach of understanding the swarming behavior of animals that occurs frequently in nature. There are considered to be two different methodologies for looking at artificial and biological systems; Analysis and Synthesis. The former is a top-down approach, and involves breaking down a complete system to gain insight into its compositional sub-systems. This approach is the classical analytical method often used in the natural sciences. Researchers concerned with Swarm intelligence tend to adopt a Synthetic (bottom-up) strategy, which means specifying the basic components of the system in great detail first, then piecing together these sub-systems to give rise to grander systems. In this context the grander system would be observing emergent behaviors when a flock of animals (sub-systems) interact together *(Cangelosi, 2002)*. Swarm Intelligence has provided a number of breakthroughs and success in recent years, compared to some other fields within AI. This is partly because it holds a significantly lower ambition than for example Strong AI; it does not seek to replicate the overwhelming mental capacity of the human brain. It simply helps us to understand the emergent properties of very simple creatures interacting together. These breakthroughs have given birth to a number of tools and algorithms being developed that have been useful in solving various problems in computer science.

What are the goals and outcomes of swarm intelligence?

As well as extending our understanding of biological systems and intelligence, a useful byproduct of swarm intelligence research is providing a very scalable and robust system model that can be applied to a number of different computing and technological problems *(Winfield, 2006)*. Smith eloquently summarizes the potential of applying the swarm model to real world applications;

> *The research in this area is flourishing as people from diverse disciplines consider the inspiration of natural colonies for solving difficult problems in design, optimization, and control. The properties of cooperation, robustness, and exploration are particularly applicable for many complex problems in engineering, science, architecture, and mathematics (Smith, 2000).*

Despite the potential that the swarm model holds in solving a variety of problems, it is important to note that many critical issues remain unsolved. A full understanding of the emergent behaviors that occur when local rules in each individual are changed is still not achieved, and often research follows a "trial and error" approach of optimizing local rules *(Bogue, 2008)*.

Put simply, swarm intelligence is the collective behavior of a population of simple agents acting independently and following a basic set of rules that dictate their actions. This often leads to the emergence of a complex global behavior, it is this emergent behavior that researchers have proved can be a successful model for problem solving in many areas. The next chapter will go on to discuss in what ways we can extract uses from the swarm paradigm and apply it to real-world problems.

Extracting uses from swarm research

In the previous chapter I described the field of swarm intelligence, what its origins are and where it lies within the larger field of artificial intelligence. It is now important to discuss in detail what useful techniques and methods specifically have been extracted from research in this field.

Despite being at an early stage of development, swarm robotics is attracting much interest from the research community. It applies the principles of swarm behavior to the field of robotics, building on a number of algorithms previously developed and inspired by natural swarms. There are considered to be two successful algorithms inspired by natural swarms; Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Both rely on social network structures to exchange information among individuals, which perhaps holds a key to the strength of these systems. This information being exchanged is commonly an indication of a food source, however the methods involved in communication vary greatly depending on the animal swarm in question. The socio-biologist E.O. Wilson notes the following when observing a school of fish searching for food:

> *In theory at least, individual members of the school can profit from the discoveries and previous experience of all other members of the school during the search for food. This advantage can become decisive, outweighing the disadvantages of competition for food items, whenever the resource is unpredictably distributed in patches (Wilson, 1975).*

This theory suggests that the sharing of information with other beings within the swarm offers an evolutionary advantage, and outweighs the disadvantage of competition for food. It is this hypothesis that is the base for the Particle Swarm Optimization algorithm being developed *(Kennedy, 1995)*.

Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, it was inspired by the social behaviour of birds flocking or fish schooling. A stochastic process is one whose behaviour is non-deterministic, meaning that the success or failure is difficult to predict, and is of a volatile nature. The outcome of the process is determined both by the predicted actions of the process, plus a random element. *(Spall, 2003)* PSO is a global minimisation technique for dealing with problems in which the best solution can be represented as a point or surface in n-dimensional space. There are a couple of underlying observations of natural swarms that informed the production of this algorithm, which I will now point out. Imagine that there is a flock of birds randomly searching for food in an area, of which there is only one piece of food. None of the birds know where the food is, however they know how far the food is after each iteration. The best strategy is to follow the neighbour who is nearest to the food. These behaviours have been replicated on a computer simulation and the result is a swarm of particles (simulated birds) with velocities "flying" through the problem space. Each particle represents a solution to the problem, and follows 2 "best" fitness values, the first being the personal best solution to the fitness function so far (called pbest). The second is the "local best" achieved by its topological neighbours. PSO also stores a value known as "gbest" that is the best solution any of the particles in the population has achieved. An optimum solution is achieved by updating generations of particles, resulting in a clustering of particles representative of the best fitness values. *(Hu, 2006)*

The algorithm has proved to be very robust and versatile, and one version, with slight variations works well in a wide variety of applications, again emphasizing the cost and time benefits over other rival systems. One such application of PSO that has aroused interest in researchers recently, is in artificial neural networks (ANN). ANN is a paradigm used by AI researchers to try and simulate basic brain functionality, and in order for it to work it has to be "trained" or taught. This is traditionally done using the evolutionary computation algorithm known as back-propagation, however several papers reported that replacing it with PSO provides faster and better results in most cases, while avoiding some of the problems previously encountered. *(Hu, 2006)* I go on to discuss some other applications of the PSO algorithm in the next chapter.

Ant Colony Optimization (ACO)

The second type of successful algorithm inspired from swarms in nature is Ant Colony Optimization, modelled on the actions of an ant colony when foraging for food. ACO is a population-based metaheuristic function that can be used to find approximate solutions to difficult optimization problems. Metaheuristic means a type of heuristic (trial and error) method for solving a general type of computational problem by combining user-defined procedures. They are mostly applied to problems that have no satisfactory algorithm or heuristic specific to that problem. Similarly to PSO, the ACO method for constructing a solution is stochastic by nature, however ACO differs to PSO by using a pheromone model, which I will explain in more detail.

Marco Dorigo is one of the founders of the ACO algorithm, and uses an example of the traveling salesman problem (TSP) to best explain how the algorithm works. The traveling salesman problem involves a number of cities each a varying distance apart from each other. The perfect solution to this problem is a closed circuit of minimal length that visits each city only once.

> *To apply ACO to the TSP, we consider the graph defined by associating the set of cities with the set of vertices of the graph. This graph is called construction graph. Since in the TSP it is possible to move from any given city to any other city, the construction graph is fully connected and the number of vertices is equal to the number of cities. We set the lengths of the edges between the vertices to be proportional to the distances between the cities represented by these vertices and we associate pheromone values and heuristic values with the edges of the graph. Pheromone values are modified at runtime and represent the cumulated experience of the ant colony, while heuristic values are problem dependent values that, in the case of the TSP, are set to be the inverse of the lengths of the edges.*
>
> *[…] Each ant starts from a randomly selected city (vertex of the construction graph). Then, at each construction step it moves along the edges of the graph. Each ant keeps a memory of its path, and in subsequent steps it chooses among the edges that do not lead to vertices that it has already visited. An ant has*

> *constructed a solution once it has visited all the vertices of the graph. At each construction step, an ant probabilistically chooses the edge to follow among those that lead to yet unvisited vertices. The probabilistic rule is biased by pheromone values and heuristic information: the higher the pheromone and the heuristic value associated to an edge, the higher the probability an ant will choose that particular edge. Once all the ants have completed their tour, the pheromone on the edges is updated. Each of the pheromone values is initially decreased by a certain percentage. Each edge then receives an amount of additional pheromone proportional to the quality of the solutions to which it belongs (there is one solution per ant).*
>
> *This procedure is repeatedly applied until a termination criterion is satisfied (Dorigo, 2007).*

This example perfectly illustrates how the Ant Colony Optimization algorithm is well suited to types of problems that require a shortest-distance type of solution. It is interesting to note how the algorithm allows the virtual "ants" to leave pheromone trails, opening communication channels with the rest of the "ants" in the swarm. This observation backs-up my earlier claim that communication between "agents" of a swarm holds a valuable key to the potential power and robustness of any swarm model.

ACO has been successfully applied to a number of real-world problems of a shortest-route nature, namely routing in telecommunication networks. AntNet is an algorithm for adaptive best-effort routing in IP (Internet Protocol) networks based on the ACO framework, and was developed by Gianni Di Caro (Ph.D) under supervision of Dr Dorigo. It was the first ACO algorithm for routing in packet-switched networks, this simply means that it is used to indentify the quickest route to send a packet of data over a network. After extensive testing in simulations and small real-world networks, it has shown to outperform several other state-of-the-art routing algorithms and has proved highly adaptive to network and traffic changes. It also carries a positive "side-effect" of automatically load balancing data, which is another problem facing networks of this kind *(Di Caro, 1998).*

The two algorithms mentioned so far are intended almost exclusively for the digital domain, e.g., computer networks and software. They offer very limited scope for usage in the physical world. Considering the physical nature of the swarms' origin, how can swarm research allow us to improve technology and devices in the physical domain as well? A clue to the answer may lie in the field of *Swarm Robotics*, which applies some of the concepts discovered in natural swarms to robotics.

Swarm Robotics

Swarm robotics is a novel approach to the co-ordination of large numbers of robots, and is inspired from the observation of social insects such as ants and termites. It relies on the same idea that a number of simple individuals can interact to create collectively intelligent systems. Erol Şahin (Ph. D) who serves on the editorial board for the journal Swarm Intelligence, proposes a starting point for a definition of swarm intelligence.

> *Swarm robotics is the study of how [a] large number of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment (Şahin, 2007).*

The abilities and "intelligent" emergent behavior of social insects is still beyond the reach of current multi-robot systems, ergo stimulating a keen interest from robotics engineers and scientists in swarm intelligence. Professor Şahin identifies that are three outstanding properties of the swarm model that is acknowledged to be desirable in robotics; Robustness, flexibility and scalability.

- **Robustness**. This means that the system has the ability to operate despite failures in individuals or disturbances in the environment. This is attributed to a couple of factors; firstly redundancy (meaning each agent/ant can be replaced by another, should a fault occur). Secondly, de-centralized coordination; meaning that destroying one part of the system will not deter the entire system's operation. Thirdly, the simplicity of individuals; having simple agents means they are less prone to failure than a single complex system.

- **Flexibility**. This requires the swarm system to have the ability to generate modularized solutions to different tasks. Ants provide a good example of this, performing a number of different tasks required of them by the hive. For example foraging for food (see chapter 1 for details), prey retrieval and forming chains with their bodies to bridge gaps. For each of these tasks, a different co-ordination system is required, reflecting the flexible nature of the system.
- **Scalability**. The system should be able to operate under a wide range of group sizes, and the functionality should not be hindered or effected.

A number of multi-million dollar research projects running world-wide attempt to implement and improve on these basic requirements using a cluster of robots, each specializing in a general type of problem. An interesting example of these projects is called Swarm-Bots *(*Mondada et al.*, 2003)* and was a study into new approaches to the design and implementation of self-organizing and self-assembling artifacts. It involved a swarm of autonomous mobile robots, called s-bots, which had the ability to connect to one another, forming a physical structure (called swarm-bot) that can solve problems the single s-bots are not able to handle. *(Trianni et al., 2004)* One such problem is 'hole avoidance', where the s-bots where encouraged to evolve the use of direct interaction and direct communication to warn other robots if they detected a hole in the ground that needed to be avoided. The researchers found that the bots evolved the ability to communicate with the other bots, providing the rest of the swarm with a sufficient warning. *(Sharkey, 2007)* It is difficult to predict where research projects such as Swarm-bots may lead us in the future, however we only need look at the number of military-funded research projects to know that they will very likely have some use in warfare, surveillance and defense. We can also look at the domains of application that swarm robotic systems might be suitable for. Professor Şahin has acknowledged four such domains that swarm robotics would specifically be suited to;

- **Tasks that cover a region**. **–** Swarm robotics would be well suited for tasks concerned with the state of space, for example environmental monitoring. The mobility of the swarm would be a beneficial factor, allowing the system to "focus" on a particular area to perform a deeper analysis or carry out necessary tasks.

- **Tasks that are too dangerous**. – The individual robots that make up a robot swarm are dispensable, meaning the system can still function when they fail or are destroyed. For purposes such as clearing a minefield, this is a far superior than having a single, expensive de-miner, that could not cover as much ground, and would prove inadequate if any fault occurred.
- **Tasks that scale-up or scale-down in time**. – The system can easily adapt if the problem-task requires a greater or lesser amount of work required, just by adding more or subtracting individual robots.
- **Tasks that require redundancy**. – Redundancy in the system allows the robotic system to degrade gracefully when single robots fail. For example if a swarm robotic system where to create a dynamic communication network in the battlefield, it would not catastrophically fail if some of the nodes where hit by enemy fire. *(Şahin, 2007)*

Findings

By detailing specifically what methods and uses researchers have extracted from swarm research, we get a clearer picture of what type of problems it can be applied to. The two algorithms mentioned; Particle Swarm Optimization and Ant Colony Optimization provide efficient and robust optimization models for problems that require both best-point and best-route type of solutions. Swarm robotics applies the basic principles taken from these algorithms to swarms of autonomous robots, and holds great potential for a magnitude of different uses, both military and domestic. Research in swarm robotics has so far yielded a good level of success, considering the infancy of the field. The Swarm-bots project has managed to produce of a swarm of autonomous robots that are able to bridge gaps and avoid obstacles by communicating and working together. Considering this was achieved over four years ago, gives some indication of the speed of progression in this field, and gives us a rough scale on which to predict future advancements.

Having identified the strengths and possible domains of application, a logical next step would be to look in more detail at a couple of examples of current swarm applications, and conclude if they are successful. This will give me a good grounding to assess if the swarm model is applicable to everyday domestic technologies.

Real-world applications of swarm intelligence

The next step to answering the goal of this dissertation is to expand on some examples of where swarm models have been applied to real world problems. Doing this gives a good indication of the current state of this technology, allowing more accurate predictions to be made about the future. It also provides a useful source of inspiration for discussing the use of this technology in a different context, specifically domestic. The previous chapter used the Swarm-Bots research project to demonstrate how the field of swarm robotics has adopted methods and findings from swarm research. It also indicates the relative infancy of this field, and suggests that the implementation of such swarm models may still be in the research and development phase. There are, however, some other applications of Swarm Intelligence that can be discussed, and their advantages over existing systems quantified. These applications can be broken down into two sections; Software & Simulation, and Hardware.

Software & Simulation

The category software & simulation covers all software implementations of ACO, PSO or any other swarm-based algorithm. It also covers solutions that involve a computer simulation or model based on the swarm paradigm. The majority of swarm-inspired applications fall under this category, and possible reasoning for this will be discussed later in this chapter. This first case study looks at the pioneering work of computer scientist Craig W. Reynolds.

- **"Boids" by Craig W. Reynolds –** This project was started in 1986 and was designed to simulate the emergent behaviour exhibited when birds or fish flock together. Reynolds believed that this emergent behaviour could be attributed to a number of simple local processes occurring in each bird (agent). He replicated the naturally occurring flocking behaviour by assigning each bird three rules to follow; separation, alignment and cohesion. By following these rules when interacting with only neighbouring flock members and the environment, realistic flocking behaviour and collision avoidance was achieved. *(Reynolds, 1987)* This pioneering breakthrough was a defining point in swarm intelligence research, and lead to the development other swarm inspired algorithms being developed (e.g. PSO and ACO). A re-incarnation of the boids model is still present in many of today's entertainment systems. Reynolds later worked on a number of movies including Tron (1982) and Batman Returns (1992) as part of the visual effects crew, implementing his flocking algorithm for use in computer generated imagery (CGI). The software company Massive have evolved Reynolds' basic system into an industrial software suite allowing filmmakers to generate crowds of thousands of realistic-acting models, and is famously used in the Lord of the Rings movies to render the battle scenes. The boids model has mainly evolved to benefit the entertainment industry, however the principles of the model have proved essential in the development of the swarm intelligence field, leading to other applications that will be now be discussed.

The next case study in this category involves a solution based upon the ACO algorithm detailed in the previous chapter.

- **American Air Liquid -** This Texas-based company supplies industrial gases to 6,000 sites throughout the USA using trucks and railcars. Some of these regions have a deregulated market causing the price to constantly be in a state of flux. The company employed the help of NuTech Solutions to provide a computer algorithm to solve their complex logistics problem. The solution developed was based on the ACO algorithm previously detailed, originally inspired by the foraging behavior of Argentine ants (Linepithema humile) that rely on a pheromone system to communicate food sources to the rest of the swarm. To find the most efficient and cost-effective options available to the company, a number of environmental variables such as: demand forecasts, manufacturing costs, weather and truck routing are fed into the system every night and four hours later they get a solution following the aforementioned principles. Charles N. Harper who oversees the supply system at Air Liquide reports huge savings to the company as a direct result of the algorithm. *(Miller, 2007)*

Another example of a solution to a real-world problem that exploits the ACO model to achieve an optimum efficiency is one employed by Southwest Airlines, again in the USA.

- **Southwest Airlines**. - The aim of this system was to improve service at Sky Harbor International Airport in Phoenix, minimizing the tarmac waiting time for the 200 aircraft a day that land on it's two runways. Doug Lawson of Southwest created a computer model of the airport whereby each aircraft had the ability to remember how long it took to get into and away from each gate, and set the model in motion to simulate a day's activity. After many simulations and providing the model with real arrival time data, each plane learned how to avoid an intolerable wait on the tarmac. *(Miller, 2007)*

Applications that use a decentralized control model may not always be explicitly inspired by swarming in nature, however could fall under the classification of Swarm Intelligence.

- **The Internet**. – Some would argue that the Internet could be classified as a model of Swarm Intelligence, as it encourages communication between connected nodes, leading to emergent behaviours. For example Wikipedia, a free online collaborative encyclopaedia that can be contributed to by anyone allows huge number of people to think together, on a scale never before possible. Thomas Malone of MIT's new Center for Collective Intelligence notes that; *"No single person knows everything that's needed to deal with problems we face as a society, such as health care or climate change, but collectively we know far more than we've been able to tap so far." (Miller, 2007)*

These applications of swarm behavior commonly deal with the optimization of existing infrastructure and systems where centralized control models have proved inefficient before them. The swarm model is well suited to these types of applications because of its robustness and fault tolerance, and lacks any hierarchical command or control structure, meaning that there is no common-mode failure point *(Bogue, 2008)*. However, the potential application of swarm intelligence is not limited to existing logical problems that can be solved with a software algorithm solution. Through research into swarm robotics, scientists and engineers could be on the brink of developing a new wave of physical technology that also employs the swarm model.

Hardware

As previously mentioned, the majority of market-ready applications that are based on the swarm model is in the domain of software simulations and optimization algorithms. The physical applications of swarm intelligence is currently greatly reliant on research in the field of swarm robotics, which has the potential to infiltrate many areas of life such as domestic, military and healthcare. Many commentators believe that the first applications of swarm robotics will lie with the military, where much of the enabling technology is being funded by American defence agencies. *(Bogue, 2007)* It is therefore wise to look at current projects and applications within this field first.

- **Military**. – *"Military agencies such as DARPA (Defense Advanced Research Projects Agency) have funded a number of robotics programs using collaborative flocks of helicopters and fixed-wing aircraft, schools of torpedo-shaped underwater gliders, and herds of unmanned ground vehicles." (Miller, 2007)* Using an example of how swarm-based control methods are being applied to autonomous flying vehicles, it is possible to demonstrate the potential of the swarm model in this area. Researchers at MIT and Boeing have developed a multiple-UAV (Unmanned Aerial Vehicle) test platform that could provide a stepping-stone for an intelligent airborne fleet that would require little human control. The research has demonstrated that the fleet of vehicles (commercially available model helicopters) can perform coordinated searching tasks over a wide area, and automatically dock with a base station to refuel when their energy runs low. The UAVs have been given functionality to autonomously provide persistent surveillance of a defined area, and are able to track and follow targets that it has identified. This demonstration of swarm coordination could eventually help yield a platform that could assist U.S. military in difficult, often dangerous, missions such as round-the-clock surveillance, search-and-rescue operations, sniper detection, convoy protection and border patrol. *(Clarke, 2006)*

Scientists have also identified that a swarm of autonomous robots would excel at assisting in a disaster crisis. For example, a swarm of search-and-rescue robots could enter the ruins of a collapsed building looking for survivors, or a swarm of UAVs could survey a disaster area from the sky, whilst simultaneously providing an ad-hoc communication network if necessary. *(Bogue, 2007)*

The next case study, does not strictly concern the application of swarm robotics, however it serves an important purpose of demonstrating that consumer robotics is viable in a domestic environment.

- **iRobot Roomba**. – This example looks at a commercially available product currently on the market that was designed to autonomously assist doing household chores, namely vacuuming the house. The Roomba, developed by the iRobot company based in Massachusetts, is a robot featuring an array of sensors and the ability to clean carpets and floors. The company has sold over three million units worldwide [9], proving to some degree that there is potential for such effort-saving devices in this market.

Again it is important to emphasize that this is not an example of swarm robotics, or Swarm Intelligence principles, it simply demonstrates the hardware abilities of current robot technology, and the acceptance of it into a domestic environment.

It is surprising to discover, that despite all of the research and investment being applied to military uses of swarm robotics, there is very little speculation or discussion regarding its usage in a domestic environment. It is commonplace for the military to drive progressions in technology, for example the ARPANET (Advanced Research Projects Agency Network) developed by the U.S. department of defense was the world's first operational packet switched

[9] According to: http://www.irobot.com/sp.cfm?pageid=203

network, and the predecessor to the Internet as we know it today. *(Abbate, 1999)* However research in this particular area yields little or no useful predictions. A report published by the National Intelligence Council (NIC) regarding the implications of disruptive technologies to the US national power over the next fifteen years identifies some possible future uses of robotics[10]. Figure 2. demonstrates that according to NIC predictions, there are few planned implementations of swarm robotics in other areas aside from military.

Application Category	Current Business	Emerging Opportunities	
		By 2015	Beyond 2020
Defense	UAVs, UGVs, Medical Robots	Military Human Augmentation Non-autonomous Combat Robots	Robot Swarms Micro Robots Autonomous Robots
Professional Service	Non-autonomous Robots	Workplace Assistance	Skilled Worker Robots
Domestic	Single-use Semiautonomous Robots	Toy Robots become Tool Robots	General Home Assistance
Healthcare	Robotic Surgery and Telemedicine Pharmacy Automation	Human Augmentation Therapeutic	Elder-Care Robots
Technology Diffusion	Assisted vehicles	Consumer Electronics`	Autonomous Vehicles

Figure 2. Timeline of robot applications (NIC, 2008)

As demonstrated by the graph, the predicted future applications of robotics in a domestic environment seems restricted to fairly uninventive stand-alone robots, eventually leading to a more generic 'home assistance' usage. It is clear that the field has possibly been overlooked for interesting applications of swarm

[10] More information regarding the assessed potential impact of robotics can be found at: http://www.dni.gov/nic/confreports_disruptive_tech.html

technology, due to financial factors or otherwise. This allows a very cautious attempt at predicting a possible application for Swarm Intelligence models / swarm robotics in a domestic environment.

Predicting domestic applications

The author is by no means qualified in any way to consider all of the technical and social implications of the proposed system, however using the description of Swarm Intelligence combined with the example case study's provided, a general concept can be suggested.

- **Water Supply Regulation in Houses.** – A problem that affects some countries is drought, whereby there is a considerable shortage of water for domestic use. A system of 'smart water valves' that could be implemented into every house in a street could be a potential solution to this. Following the same simple local processes discussed in earlier chapters, each 'smart water valve' could communicate with neighbouring houses and attempt to align the level of water in the reserve tank with that of its neighbours. The emergent behaviour of many houses doing this might lead to a more evenly distributed supply of water to homes, and potentially prevent cuts in the supply.

This particular solution might not be suitable in many domestic scenarios, however it demonstrates that a swarm model applied to housing services could lead to positive emergent behaviors on a local or national scale. The repercussions of such positive effects on a national scale could have the potential to change current trends in energy wastage, and be at the crux of a more energy-efficient era.

Summary

Using these case studies is important to communicate the current saturation of Swarm Intelligence theory and models into real-world applications. Breaking down these applications into software & simulation and hardware, unveils that they are at vastly different levels of saturation. Software models and simulations based on observations of natural swarms have been maturing over the past twenty years, and have been developed into useful tools for the entertainment industry and telecommunications industry to mention a few. However, hardware incarnations of models loaned from the Swarm Intelligence field are only very recent, and are still in the early stages of research and development. Currently the only field that explores the implementation of swarm-based methods into hardware is the field of swarm robotics, which according to current trends favors a future predominantly in military uses. By providing an informed speculation of a possible domestic application of the swarm model, the advantages of such a system on a local and national scale can be demonstrated. It is also possible to illustrate that the domestic environment is ready for this type of robotic technology, by using an example of the autonomous house-cleaning robot Roomba.

Findings and Conclusions

Looking at human, animal and artificial intelligence, a general observation can be made that discrete computers and animals hold something in common with each other. Both perform relatively simple pre-programmed functions in a specific domain. Despite sometimes performing these tasks exceptionally well, they both lack the superior 'general intelligence' possessed by human beings, allowing us to understand abstract concepts, manipulate thoughts and apply reasoning to formulate plans. Research shows that this could be due to our grasp of language and symbols, which animals do not have. However, when animals swarm or flock together, a number of advanced tasks can be achieved that would not be possible for a single animal. These tasks or functions benefit the entire swarm, and provide an evolutionary advantage over 'flying solo'. It is this intelligent emergent behavior in nature that inspires the field of Swarm Intelligence, which is concerned with understanding the collective behavior of decentralized, self-organized systems, typically made up of a population of agents following simple rules interacting locally with each other and their environment.

The Boids simulation developed by Reynolds played a key role in determining the local processes at play in naturally occurring swarms. Even though the simulation was only intended to reproduce the movement of animals in flocks, it has made a considerable contribution to the entertainment industry, providing an effective software model for creating computer-generated (CGI) crowds in movies and TV. Reynolds' model paved the way for more research in this field, ultimately leading to the development of the Ant Colony Optimization and Particle Swarm Optimization algorithms. These algorithms have been the brick and mortar for a number of software solutions such as adaptive routing in telecommunication networks, and achieving efficiency in logistics systems. For these uses they have been quantifiably proven to hold a number of advantages over alternative state-of-the-art algorithms. These advantages are universally observed throughout almost any implementation of a swarm-based system, and consist of;

- Robustness – The system can still operate despite individual failures.

- Flexibility – The system can generate modular solutions to different tasks.
- Scalability – The operation of the system is not effected by size of swarm.

However, the application of Swarm Intelligence principles is not confined to software simulations and algorithms, and through the field of swarm robotics we can approach problems and tasks in the physical domain using a similar swarm model. By looking closer into the field of swarm robotics it is possible to extract what domains of application it is best suited, these being;

- Tasks that cover a region.
- Tasks that are dangerous.
- Tasks that scale-up or scale-down in time.
- Tasks that require redundancy.z

Knowing the domains of application for swarm robotics is important because it allows a deeper understanding of the type of conditions it is best suited to.

Analyzing some case studies of applications based on the principles of Swarm Intelligence, two definitive conclusions can be drawn; firstly, that software simulations and algorithms are considerably more saturated in real-world applications as opposed to hardware implementations. We see the product of swarm-based software in many high-budget movies and computer games, used to generate realistic crowds of people or models. This imbalance could be caused by a number of reasons; development cost, development time, lack of hardware requirements, or simply that swarming was simulated in software years before the principles where applied to robotics.

The second conclusion finds that the vast majority of anticipated uses for swarm robotics are in the military. This is no surprise as many research projects in this area are funded by various US military agencies, namely DARPA, and if past technology trends are anything to go by it is not uncommon for military research to lay the path for widespread saturation of a technology (see the Internet[11]). There is very little consideration or discussion for applications of swarm robotics or any other hardware implementations of a swarm-based model in a

[11] For more information about the internet see: *Inventing the Internet* by Abbate, J.

domestic environment. This raises the question; why not? Could it be that the domestic environment doest not provide any of the aforementioned desirable domains of application? Is the field of swarm robotics not developed enough for the potential in this area to be exploited? Or is it simply that we are yet to gain a full understanding of swarming behavior and are not used to solving problems using a decentralized approach? Some researchers believe this could be the case, as Eric Bonabeau, a complexity theorist and the chief scientist at Icosystem Corporation in Cambridge, Massachusetts, explains using traffic as an example.

> *We don't even know yet what else we can do with this, we're not used to solving decentralized problems in a decentralized way. We can't control an emergent phenomenon like traffic by putting stop signs and lights everywhere. But the idea of shaping traffic as a self-organizing system, that's very exciting (Miller, 2007).*

Despite the lack in complete understanding of the emergent properties of swarm behavior, it is still possible to initiate discussion and begin applying the model to different situations, as demonstrated by the military research in this area. Having identified that the domestic environment does in fact posses some suitable domains of application, it is reasonable to suggest a possible domestic hardware application that utilizes the previously discussed principles of Swarm Intelligence. Doing this proves that the swarm paradigm has potential for use in domestic technology, despite the lack of discussion and research in this area.

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