1 Introduction

Over the last 50 years, robotic and automation systems have transformed our world and greatly enhanced the quality of our daily life. With the development of science and technology, many intelligent systems which integrate machines, electronics, automatic control and information technologies have emerged. Such systems can accomplish numerous tasks originally performed by humans and often prove superior in terms of precision, speed and cost. For example, they can replace humans in the tasks that require repetitive and monotonous operations as well as those experiments conducted in dangerous environments (e.g, nuclear factory) which are hazardous to human beings or some operating environments that may be beyond humans' capabilities of reach (e.g, Mars). In 2003, two famous robots—*Spirit* and *Opportunity* were sent to Mars by NASA to explore the surface and geology of Mars [1].

Robotic and automation systems also contribute to the science field, especially in the data-driven science [2] in which researchers have to deal with a huge amount of data collected in the experiments. With the help of intelligent/robotic systems, researchers can collect data much faster than ever before. For instance, the high-throughput screening (HTS) system [3], which is widely used in the drug discovery and chemistry, allows the researchers to conduct millions of experiments and collect data in a very short time. Besides data collection, the system can also analyze the data automatically using intelligent software, which provides an ideal tool for data analysis in scientific research and free researchers from the tedious and monotonous process of data analysis if done manually. This increases the speed of scientific research to a great extent.

Intelligent systems also play an important role in other science fields such as *ethology*, which is the scientific study of animal behavior [5]. Ethology is pursued not only because it is a subject of interest in itself, but also because the knowledge gained from it has several practical applications. For instance, models of animal decision-making processes can be used to predict their behavior in novel environments, which can help in making ecological conservation policy [6]. Knowledge about animal behaviors has also been applied for solving computational problems [7], and for constructing biologically-inspired robotic agents [8]. There are four types of questions to be investigated in ethology: questions concerning causes, functions, development and evolution [5]. Causes refer to the mechanisms of animals that are innate as well as the external/internal stimuli that affect such behavior. Functions concern what is the purpose of this behavior, for example, foraging or matting. The development of animal behavior deals with how animals learn such behavior during their whole life as well as how such behavior is affected by experience, while evolution relates to how the behavior changes over generations in the course of natural evolution. Over centuries, these four questions have been investigated by ethologists either in a well-controlled laboratory or an outdoor environment, which helps humans better understand nature. The ultimate goal of this thesis is to contribute to the study of animal behavior through developing an intelligent system for investigating the first two types of questions: causes and functions.

1.1 Motivation

Although intelligent and automation systems have played an significant role in scientific research, they are often secondary. In most of the cases, these machines are simply doing mechanical and repetitive work. The question is whether we can build a machine/system that can dominate the whole process of scientific investigation and automatically analyze experimental data, search for correlation between different elements, and generate new hypotheses. In other words, can we build a system which is able to automatically conduct scientific experiments without (or with minimal) human intervention? Recently, the emergence of "robot scientists" shows that such systems are within reach [9, 10, 11]. Following this motivation, this thesis aims to pave the way for further development in science automation [10], especially in the area of animal behavior study. In particular, we present a metric-free method—*Turing learning*, that can automatically learn/model agent behavior[1] with minimal human intervention.

System identification, which is a process of modeling natural or artificial systems through observed input and output data, is an effective method of investigating agent behavior (artificial agents or animals). It has drawn a large interest among researchers for decades [12]. Many studies have investigated how to deduce rules of agent behavior

[1]Since the behaviors under investigation in this thesis are simulated using computer simulation or physical robots, throughout the thesis, unless otherwise stated, we used the term agent behavior.

using system identification techniques based on macro models [13]. When investigating the interaction within a group of agents and between the agents and environments, agent-based models [14] provide a good representation of such behaviors. Agent-based model is a type of micro model, in which the individual rules are designed, and the global behavior emerging from interaction is used for refining the models. Evolutionary computation which draws inspiration from biological evolution (introduced in detail in Section 2.2) has been shown to be a powerful method to automate the modeling process especially for behaviors that are hard to formulate [15, 16]. Evolutionary computation provides a potential realization for automation science, as the models evolve in an autonomous manner. Therefore, it is the main technique that is investigated in this thesis for performing system identification.

A limitation of current system identification methods is that they rely on predefined metrics, such as the square error, to measure the difference between the output of the models and that of the system under investigation. Model optimization then proceeds by minimizing the measured differences. However, for complex systems, defining a metric can be non-trivial and case-dependent. It may require significant prior information about the systems. Moreover, an unsuitable metric may not distinguish well between good and bad models, or bias the identification process. This thesis overcomes these problems by introducing a system identification method that does not rely on predefined metrics, which allows a machine to infer the agent behaviors in a fully automatic way.

Our approach uses a coevolutionary algorithm (which will be introduced in detail in Section 2.2) comprised of two populations. The first population contains *models*, which are executed by replicas/animats. The second population contains *classifiers*. The populations co-evolve competitively. The fitness of the classifiers depends solely on their ability to distinguish the behavior of the replicas from the behavior of the agents under investigation. The fitness of the models depends solely on their ability to mislead the classifiers into making the wrong judgment, that is, classifying them as the agent. In this way, the approach does not require any predefined metrics to quantify the difference between the behaviors of models and agents. Our method is inspired by the Turing test [17, 18], which machines can pass if behaving indistinguishably from humans. Similarly, the models, which evolve, can pass the tests by the co-evolving classifiers if behaving indistinguishably from the agents. We hence call our method *Turing learning*. To the authors' knowledge, *Turing learning* is the first system identification method that does not rely on pre-defined metrics.

1.2 Problem Statement

Turing learning allows a machine to infer agent behavior in a fully autonomous way. To demonstrate the merits of this method, three case studies are presented.

In the first case study, the method is used to automatically learn swarm behaviors, which are emergent behaviors that arise from the interactions of numerous simple individuals [19]. Modeling swarm behaviors using predefined metrics could be non-trivial, as the individuals not only interact with the environment but also with each other. Typically, their motion appears stochastic and is hard to predict [20]. For instance, given a swarm of simulated fish, we would have to evaluate how close its behavior is to that of a real fish swarm, or how close the individual behavior of a simulated fish is to that of a real fish. This is difficult, as characterizing behavior at the level of the swarm (that is, an emergent behavior) typically requires domain-specific knowledge and may not discriminate among alternative individual rules that exhibit similar collective dynamics [21]. Characterizing behavior at the level of individuals is also difficult, as even the same fish in the swarm is likely to exhibit a fundamentally different trajectory every time it is being looked at. In our approach, the classifiers substitute for the metrics, which are thus products of the coevolution. The system learns the swarm behavior through observation.

In the second and third case studies, the method is applied to learn deterministic and stochastic behaviors of a single agent, respectively. In these case studies, the agent to be studied is put in an environment. The classifiers have full control over the environmental stimuli that the agent responses to, and at the same time observe the agent's actions. In this theis, the classifiers only observe the agent's motion which is the simplest case. The system identification task is to learn the observed behavior, in other words, the agent's actions in response to the environmental stimuli. The classifiers construct on-the-fly patterns of stimuli that help reinforce the learning process, so that the system can automatically extract the model of the agent behavior. This interactive approach proves superior to learning through passive observation.

1.3 Contributions

- A metric-free coevolutionary approach to learn agent behaviors in an autonomous manner. It does not rely on predefined metrics to gauge the difference between the behaviors of agents and inferred models. This eliminates potential bias that predefined metrics may have on the solutions obtained.

- A coevolutionary system to automatically perform system identification directly through observation of swarms of physical robots and the results obtained using a swarm of e-puck robots.

- A coevolutionary system that can automatically learn the deterministic behaviors of a single agent in simulation by interacting with it, rather than simply observing its behavior in a passive manner. This interaction can help the machine to extract all of the agent's behavioral dynamics through outputting a complex sequence of input which is difficult to generate by random input.

- A coevolutionary system that can automatically learn the stochastic behaviors of a single agent in simulation through controlled interaction. In this case, outputting a fixed sequence of input is not sufficient for the machine to extract all the information from the agent due to its stochastic features. Instead, the system learns to interact with the agent through changing the environmental conditions (stimuli) based on the behavioral dynamics of the agent during the experimental process. The results are shown to be better than those obtained using metric-based system identification methods.

1.4 Publications

This thesis presents the author's own work. Some parts of the thesis have been published as original contributions to the scientific area. A preliminary work of Chapter 3 was orally presented in a conference by the author:

- **W. Li**, M. Gauci and R. Groß, "Coevolutionary learning of swarm behaviors without metrics," *Proceedings of 2014 Genetic and Evolutionary Computation Conference (GECCO 2014).* ACM Press, Vancouver, Canada, 2014, pp. 201–208.

A preliminary work of Chapter 5 was orally presented in a conference by the author of this thesis:

- **W. Li**, M. Gauci and R. Groß, "A coevolutionary approach to learn animal behavior through controlled interaction," *Proceedings of 2013 Genetic and Evolutionary*

Computation Conference (GECCO 2013). ACM Press, Amsterdam, Netherlands, 2013, pp. 223–230.

A part of the Chapter 3 and Chapter 4 has been written as a paper and ready to be submitted to the following journal.

- **W. Li**, M. Gauci, J.Chen and R. Groß, "Reverse Engineering Swarm Behaviors Through Turing Learning," *IEEE Transactions on Evolutionary Computation*, in preparation.

Apart from the work presented in this thesis, the author has also been involved in some other projects which were conducted in the Natural Robotics Lab, at the University of Sheffield, UK. This leads to several publications in the following journals and conference:

- M. Gauci, J. Chen, **W. Li**, T. J. Dodd, and R. Groß, "Self-organized aggregation without computation," *The International Journal of Robotics Research*, vol. 33, no. 8, pp. 1145–1161, 2014.

- J. Chen, M. Gauci, **W. Li**, A. Kolling and R. Groß, "Occlusion-based cooperative transport with a swarm of miniature mobile robots." *IEEE Transactions on Robotics*, vol.31, no.2, pp. 307–321, 2015.

- M. Gauci, J. Chen, **W. Li**, T. J. Dodd, and R. Groß, "Clustering objects with robots that do not compute," in *Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014)*. IFAAMAS Press, Paris, France, 2014, pp. 421–428.

The author also conducted a project as a research fellow in the Department of Mechanical Engineering, University of Western Ontario, Canada, where he developed the idea of Mechanical Cognitivization. This leads to one publication in the following journal:

- G. Avigad, **W. Li**, A. Weiss, "Mechanical Cognitivization: A Kinematic System Proof of Concept" *Adaptive Behavior*, vol.23, no.3, pp. 155–170, 2015.

1.5 Thesis Outline

This thesis is structured as follows:

- Chapter 2 describes the background of the thesis as well as the related work presented in the literature.

- Chapter 3 introduces the metric-free method—*Turing learning*. It is applied to learn two swarm behaviors (self-organized aggregation [22] and self-organized object clustering [23]) through observation. Section 3.6.1 systematically analyzes the evolution of models, through objectively measuring the evolved models in terms of local and global behaviors. Section 3.6.2 investigates the coevolutionary dynamics. Section 3.6.3 analyzes the evolved classifiers and discusses how to construct a robust classifier system that could be used for detecting abnormal behaviors in the swarm. Section 3.6.4 studies the effect of observing only a subset of agents in the swarm and the results obtained. Section 3.6.5 presents a study where the agent's morphology (field of view) and brain (controller) are inferred simultaneously. Section 3.6.6 also applies the method to learn other swarm behaviors. Section 3.7 summaries the findings in this chapter.

- Chapter 4 introduces a physical system to perform system identification using the *Turing learning* method. We present a case study using swarms of physical robots. Section 4.1 presents the physical platform, including robot arena, robot platform. Section 4.2 introduces the motion tracking system. Section 4.3 describes the PC and Robot programs. Section 4.4 presents the experimental setup used for inferring the physical robot swarm behaviors. Section 4.5 discusses the results obtained. Section 4.7 summaries the findings in this chapter.

- Chapter 5 presents two case studies to learn the deterministic and stochastic behaviors of a single agent, respectively. In these case studies, the system not only observes the behavior of the agent but also interacts with the agent through changing the stimulus that can influence the agent's behavior. Section 5.3.1 describes the deterministic behaviors under investigation. Section 5.3.3 discusses the results obtained for learning the deterministic behaviors. Section 5.4.1 presents the stochastic behaviors under investigation. Section 5.4.3 and Section 5.4.4 discuss the results obtained for learning stochastic behaviors. Section 5.5 summaries the findings in this chapter.

- Chapter 6 concludes the thesis and discusses the future work.