Chapter 18 Time and Frequency Analysis of Particle Swarm Trajectories for Cognitive Machines

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ABSTRACT

This paper examines the inherited persistent behavior of particle swarm optimization and its implications to cognitive machines. The performance of the algorithm is studied through an average particle's trajectory through the parameter space of the Sphere and Rastrigin function. The trajectories are decomposed into position and velocity along each dimension optimized. A threshold is defined to separate the transient period, where the particle is moving towards a solution using information about the position of its best neighbors, from the steady state reached when the particles explore the local area surrounding the solution to the system. Using a combination of time and frequency domain techniques, the inherited long-term dependencies that drive the algorithm are discerned. Experimental results show the particles balance exploration of the parameter space with the correlated goal oriented trajectory driven by their social interactions. The information learned from this analysis can be used to extract complexity measures to classify the behavior and control of particle swarm optimization, and make proper decisions on what to do next. This novel analysis of a particle trajectory in the time and frequency domains presents clear advantages of particle swarm optimization and inherent properties that make this optimization algorithm a suitable choice for use in cognitive machines.

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1. INTRODUCTION

One of the goals of a cognitive system is to emulate the behavior of human cognition (Wang, 2002; Wang, Zhang, & Kinsner, 2010). There are several cognitive systems that are being implemented at different levels of complexity, including cognitive radio (Haykin, 2005; Haykin, Reed, Li, & Shafi, 2009a, 2009b), cognitive radar (Haykin, 2006), and cognitive networks (Hossain & Bhargava, 2007). All these examples of cognitive systems share four phases used to (1) acquire, (2) process, (3) interpret, and (4) express information for actions (Wang, 2002). The acquisition phase consists of sensors gathering data from both the environment and other interacting systems or living creatures, as well as the system itself. This phase is also responsible for representing the data to maximize the efficiency of the subsequent phases. Failure to pick a suitable representation can have a significant effect on the performance of the cognitive machine (Gavrilova, 2009). The second phase of the system is to process the raw data by extracting the useful information from the system, and to perform pertinent computations to determine how the cognitive machine is to act in the future. As described in (Kinsner, 2004), the processing and interpreting of information must be done at multiple scales in order to extract the pertinent features for very general and very specific decision making processes. The main objective of the multi-scale analysis is to reveal any long-term correlations in the behavior or the underlying processes that can be used to classify and/or improve the performance of the system (Kinsner, 2004). Cognitive processes are considered to be inherently long-range dependent since the environment in which systems is placed also experiences a long-range correlated behavior. The interpretation phase determines which actions to execute in which order and finally, the last stage expresses the decisions in ways that can be conveyed to other parts of the system (actuators) and, in some cases, to a user.

As part of the processing and interpretation stages, a cognitive system must be able to look at large amounts of data and make quick (often faster than real time, or hyper-real time) decisions on what to do next. The decision process often requires more alternatives to be considered in a short window of time than it is physically possible for a real-time system (Kinsner, 2004). Thus, in order to make good decisions without exploring all possible paths, a cognitive system requires optimization techniques that can survey the possible options, and quickly select the best or most suitable option possible. Furthermore, given the long-term dependence found in cognitive machines, an optimization algorithm that can reveal correlated behaviors can help better predict future behaviors.

There are many applications of this research. For example, scheduling tasks on multi-core systems for space applications requires an intelligent system capable of autonomously reading status information on the system to select which routines to execute in order to keep the satellite operational. The status of the components can be used as drivers for the evolutionary algorithm to schedule tasks even when unpredictable situations arise (i.e., one processor fails). Furthermore, in these real-time applications, one cannot allocate tasks dynamically using near-optimal schedules. Therefore, long-term correlations about the system and an intricate knowledge of the behavior of the satellite can be used in predictive scheduling to maximize the use of available resources.

This paper first reviews the requirements for an ideal optimization technique for use in cognitive systems, and uses a novel analysis of a *particle swarm optimization* trajectories in the time and frequency domains to show how the algorithm is inherently designed to satisfy these requirements.

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