

**MULTI-OBJECTIVE EVOLUTION OF RF-SIGNAL
HOMING BEHAVIOR IN SIMULATED
AUTONOMOUS WHEELED ROBOTS USING
DIFFERENTIAL EVOLUTION**

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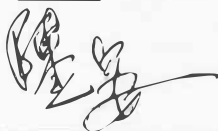
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ABSTRACT

MULTI-OBJECTIVE EVOLUTION OF RF-SIGNAL HOMING BEHAVIOR IN SIMULATED AUTONOMOUS WHEELED ROBOTS USING DIFFERENTIAL EVOLUTION

Although there are more than 1 million robots occupying the world today in the automotive and materials handling industries, a large majority of these robots are fixed robots which are equipped with hand-engineered, pre-programmed routines to function within a static, predictable environment. Only a small fraction (0.15%) of this total comprises of autonomous mobile robots that have artificial intelligence and which can be adaptive to changing, dynamic environments. This is mainly due to the difficult task of synthesizing effective yet robust controllers for autonomous mobile robots. As such, evolutionary robotics (ER) has been introduced as a new methodology to overcome these limitations by applying artificial evolutionary optimization algorithms for the automatic generation of robotic controllers. Over the last decade, a number of successful studies have been reported in the application of ER. However until very recently, only single-objective evolutionary algorithms have been utilized in ER. In the few investigations that have utilized evolutionary multi-objective algorithms (EMO), the studies have only been conducted on highly abstract, legged robots. Hence, the motivation for this thesis is three-fold; firstly to investigate whether EMO can be successfully applied to ER on simulated but actual, real-world physical wheeled robots, secondly whether EMO can be applied to ER for generating radio-frequency (RF) localization behaviors, and lastly whether EMO can be applied to ER for generating useful behaviors in multiple robots working as a collectively-intelligent group. The experiments are implemented to focus on five main research objectives: (1) to obtain a fitness function for generating the wheeled robot's RF-localization behavior in an inherently noisy environment; (2) to evaluate the EMO's performance in evolving the required robot's controllers to solve the task environment; (3) to test the evolved controllers' robustness; (4) to verify the EMO's ability to generate useful controllers in a collective task; and (5) to analyze the evolved controllers' internal processing structure in terms of Hinton graphs. The results showed that: (1) a fitness function was successfully generated for the wheeled robot's RF-localization behavior; (2) the EMO performed reliably in synthesizing the required controllers for solving the task environment; (3) the evolved robot controllers were robust to the different, previously unseen testing environments that were different from the evolution environment; (4) the EMO was able to evolve controllers for solving a collective box-pushing task for multiple robots; and (5) based on the Hinton graph analysis, there were noticeably strong excitatory as well as inhibitory synapses present in the most optimal evolved controllers that produced the desired robot behaviors. Therefore in conclusion, this thesis has shown that EMO is a useful and promising technique to employ in ER for automatically generating robust RF-localization behaviors in simulated autonomous wheeled robots as well as for collective behaviors in multiple robot environments.

ABSTRAK

Kini, terdapat lebih daripada satu juta robot yang beroperasi di dunia, akan tetapi majoriti besar robot yang terdapat dalam pasaran adalah terdiri daripada robot tetap yang digunakan dalam bidang automotif dan industri pengendalian bahan. Robot tersebut dilengkapi dengan kejuruteraan manual dan rutin pengaturcaraan yang beroperasi secara statik dalam persekitaran yang diketahui. Hanya segelintir robot autonomik (0.15%) dilengkapi dengan kecerdasan buatan yang dapat menyesuaikan diri dalam persekitaran lain. Ini adalah kerana pelaksanaan mensintesiskan pengawalan robot automatik yang berkemampuan tinggi adalah rumit. Maka, evolusi robotik (ER) telah diperkenalkan untuk mengatasi limitasi berkenaan dengan menggunakan algoritma evolusi dalam membangunkan pengawal robot autonomik. Banyak penyelidikan yang berjaya telah dilaporkan setelah pendedahan kepada pengetahuan ER. Walaubagaimanapun, hanya algoritma evolusi satu objektif yang sering digunakan dalam penyelidikan tersebut. Beberapa penemuan baru telah mengaplikasikan algoritma "*evolutionary multi-objective (EMO)*" tetapi penyelidikan tersebut hanya dilaksanakan pada robot berkaki yang maya. Maka, motivasi penyelidikan tesis ini dibahagikan kepada tiga bahagian: pertama adalah untuk menentukan sama ada "*EMO*" dapat berjaya diaplikasikan dalam ER untuk simulasi robot beroda yang nyata fizikalnya, yang kedua adalah untuk menentukan kebolehan "*EMO*" dalam pengaplikasian ER untuk menghasilkan sifat penetapan radio-frekuensi (RF), dan akhir sekali adalah untuk menentukan kebolehan "*EMO*" dalam pengaplikasian ER untuk menghasilkan sifat yang berguna dalam persekitaran berbilang robot yang berfungsi dengan cerdas secara berkumpulan. Eksperimen-eksperimen dilaksanakan dengan memfokuskan kepada lima objektif utama: (1) membangunkan satu fungsi penyesuaian bagi menghasilkan pengawal tingkah laku penetapan RF bagi robot beroda; (2) untuk menilai pencapaian "*EMO*" dalam pengevolusian pengawal robot yang diperlukan; (3) menguji keteguhan pengawal yang telah berjaya dievolusikan; (4) mengenalpasti kebolehan "*EMO*" dalam menghasilkan pengawal yang berguna dalam tugas yang melibatkan robot berkumpulan; serta (5) menganalisa struktur dalaman pengawal yang telah dievolusikan dengan menggunakan teknik Hinton. Keputusan yang dicapai menunjukkan bahawa: (1) satu fungsi penyesuaian telah berjaya dibangunkan untuk tingkah laku penetapan RF bagi robot beroda; (2) penggunaan "*EMO*" berjaya dalam mensintesiskan pengawal yang diperlukan; (3) pengawal robot dapat menyesuaikan diri dalam persekitaran yang berbeza, yang sebelum ini tidak pernah disintesiskan dan digunakan dalam persekitaran yang terlibat dalam pengevolusian; (4) "*EMO*" telah dibuktikan dapat menghasilkan pengawal yang digunakan untuk menyelesaikan tugas penolakan kotak secara berkumpulan yang melibatkan sebanyak lima robot; (5) berdasarkan kepada analisa graf Hinton, ianya jelas menunjukkan bahawa struktur dalaman bagi pengawal-pengawal robot yang dibangunkan mencerminkan kepada kelakuan dan tindak balas gerakan robot. Secara kesimpulannya, tesis ini telah menggambarkan bahawa "*EMO*" adalah teknik yang berguna dan berpotensi untuk digunakan dalam bidang ER bagi menghasilkan pengawal bersifat penempatan RF yang dapat menyesuaikan diri dalam simulasi robot beroda autonomik dengan sifat bekerja berkumpulan dalam persekitaran berbilang robot.

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LIST OF ABBREVIATIONS

3D	3 Dimension
AI	Artificial Intelligence
ANN	Artificial Neural Network
DE	Differential Evolutionary
EA	Evolutionary Algorithm
EC	Evolutionary Computing
EMO	Evolutionary Multi-Objectives
EP	Evolutionary Programming
EPFL	Ecole Polytechnique Fédérale De Lausanne
ER	Evolutionary Robotics
ES	Evolution Strategy
GA	Genetic Algorithm
GP	Genetic Programming
ISO	International Organization for Standardization
PDE	Pareto-frontier Differential Evolutionary
PDE-ER	Modified Pareto-frontier Differential Evolutionary Algorithm in Evolutionary Robotics Perspective
RF	Radio-Frequency
USD	United State Dollar



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LIST OF SYMBOLS

ω_{ih}	Weight of inputs
ω_{ho}	Weight of outputs
I	Number of input neurons
H	Number of hidden neurons
O	Number of output neurons
$f(x)$	Function
U	Uniform Distribution
G	Gaussian Distribution
ρ	Binary vector
α	Parent
S	Signal source score
t/T	Time
i	Highest distance sensor activity
V	Average wheels speed
W_L	Left wheel speed
W_R	Right wheel speed
B	Box sensor value



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CHAPTER 1

INTRODUCTION

1.1 Overview

There are more than one million industrial robots that are occupying the world today in an industry that is estimated to be worth around USD 18 billion annually and growing (IEEE, 2008). A large majority of these industrial robots are actually fixed or attached robots mainly deployed in the automotive and materials handling sectors. The working parameters of these robots are highly constrained where their controllers are usually pre-programmed and hand-engineered since the routines are only required to function within a restricted environment that is both static and predictable as well as highly controlled (Nolfi and Floreano, 2000).

Furthermore, only a small fraction of industrial robots comprise of fully autonomous mobile robots (Pelletier, 2008). An industrial robot is defined as an automatically-controlled, reprogrammable, multipurpose manipulator programmable in three or more axes machine (Nof, 1999). An autonomous mobile robot is defined as mobile machines or wheeled machines that are equipped with Artificial Intelligence (AI) and capable to perform desired tasks in unstructured environments without continuous human guidance (Nolfi and Floreano, 2000). Major differences between the industrial robots and autonomous mobile robots are the capability of its movement and response to the environment. Industrial robots are fixed or attached robots whilst autonomous mobile robots are mostly wheeled (or to a much lesser extent legged) robots that can move around in completing the desired tasks. On the other hand, industrial robots require either indirect or direct human intervention whereas autonomous mobile robots are able to complete tasks independently without any human interventions.

The programming of such autonomous robots are significantly more complex and difficult compared to fixed or attached robots mainly due to their much larger scope of operational requirements that require both intelligent and adaptive behaviors in a working environment that is dynamic, possibly unknown

and highly unpredictable. The field of Evolutionary Robotics (ER) was proposed in order to overcome some of the difficulties of hand-programming autonomous robot controllers (Nolfi and Floreano, 2000). The basic idea in ER is to apply artificial evolutionary optimization algorithms to automatically synthesize and optimize artificial neural network (ANNs) controllers that are able to generate the required behavior for the autonomous robots. ANN is a computational model based on biological neural networks that consists of an interconnected group of artificial neurons which can be practically used in prediction, classification, control problems and approximation. In other words, ANN is an adaptive system that changes its structure based on internal or external information that flows through the network during its learning phase.

In just over a decade, significant progress has been made in the field of ER and its application to the automatic synthesis of autonomous robot controllers (Nolfi and Floreano, 2000). However, practically all of the reported studies relied on single-objective Evolutionary Algorithms (EAs) to conduct this artificial evolution process (Floreano *et al.*, 2004). EA is a sub-topic of evolutionary computation and is a generic population-based metaheuristic optimization algorithm (Refer to Chapter 2, Section 2.5 for detailed discussion). A single-objective EA is a type of EA that is capable to solve only one objective in a single run (Coello Coello, 2005). Hence, there is only one solution found when such a technique is used. Furthermore, the main task has been reported in majority of ER studies focus on generating some light-following behaviors or commonly known as phototaxis (Christensen and Dorigo, 2006; Christensen *et al.*, 2007), and obstacle avoidance (Floreano *et al.*, 2004) for single robots only. The robots that are equipped with phototaxis behavior are capable to seek for and navigate towards the light source whilst robots that are equipped with obstacle avoidance behaviors are capable of avoiding from bumping in to any walls or obstacles that are in the environment. Although some researchers have successfully shown promising results in evolving robot controllers using single-objective EAs (Floreano *et al.*, 2004; Christensen *et al.*, 2007), there are still opportunities in terms of further improving the controllers that have already been developed. The controllers that are generated using a single-objective EA is only capable to perform a very limited and highly specific task rather than cooperate together in completing a complex task such as box-pushing or formation marching.

Furthermore, it is limited to only one solution that can be obtained with the single-objective EA used in generating the required robot controllers in any single run. Hence, some researchers have proposed Evolutionary Multi-objective Optimization (EMO) algorithms in order to overcome such limitation found in single-objective EAs, where EMO refers to optimization algorithms that are able to generate multiple Pareto-optimal solutions that trade-off between two or more distinct and conflicting objectives in a single run of the EMO algorithms (Deb, 2002; Coello Coello, 2005).

Some researchers have been initiated into the use of EMOs (Teo, 2003; Capi, 2007) algorithms for ER applications although these limited studies only utilized highly abstract simulations of legged artificial creatures that do not have any real-world counterparts (Teo, 2003; Parrott et al., 2005; Capi, 2007). EMO is well known as one of the evolutionary computing methods that are able to simultaneously optimize two or more conflicting objectives subject to certain constraints (Deb, 2005). Hence, this is extremely beneficial in ER studies since rather than evolving robot controllers using single objective methods, a set of multiple Pareto-optimal solutions can be obtained using EMOs used rather than just a single solution if single objective methods were used. Furthermore, multiple objectives can be optimized in the same run without having to modify the weights if a weighted-sum approach is used in single objective methods.

Therefore in this thesis, the main motivation is to fill some of these gaps in the literature as well as to explore previously untested areas of application for ER. Firstly, the proposed research will attempt to answer the question of whether EMO can actually be practically applied for the successful synthesis of ANN controllers for simulated but actual, physical autonomous wheeled robots that exist in the real world. One of the most popular EMOs, as named Pareto-frontier Differential Evolutionary (PDE) multi-objective optimization is considered and used in this study since it has been previously shown to work well in evolving abstract legged creatures (Teo, 2003). The PDE is a term that refers to hybridization of the EMO approach into the Differential Evolution algorithm (DE) which utilizes the Pareto-frontier selection methodology (Abbass and Sarker, 2002). The Pareto-frontier selection method or Pareto set selection is the set of choices that is Pareto efficient (Abbass and Sarker, 2002).

Secondly, the proposed research will investigate whether EMO can be applied in ER to successfully generate a behavior that has thus far never been explored, which is radio frequency (RF) localization. RF-localization is a kind of taxis behavior that occurs when an organism navigates in response to the propagation of radio frequency. This is advantageous for some organisms or animals such as insects and birds to orient towards themselves for tracking their mate during mating session. Such a localization behavior would prove immensely useful in search-and-rescue operations, some of which are now already relying heavily on the radio frequency technology (Christensen *et al.*, 2007). Comparing against light-following behavior (which is also known as phototaxis), robots that are evolved with light following behaviors are limited in their tracking capability due to light's unique characteristic that makes it unable to propagate through any solid object whilst such limitations can be overcome with the use of RF signals. An RF signal can propagate through any immediate objects within a certain distance. Furthermore, an RF signal is able to propagate longer distances compared to a light source. Consequently, in the SETI Institute, practically all of the research programs uses radio signals to find evidence of extraterrestrial life rather than depending on light-based telescopes (Glory, 2004). Moreover, radio signal technology is now widely utilized in current search-and-rescue operations (Pike, 2003).

Thirdly, the proposed research will also investigate whether EMO can be again applied to ER for the generation of useful behaviors in environments with multiple robots that need to work as a collective intelligence with group robotics behavior in accomplishing the box-pushing task. The collective robotics behavior refers to a group of robots that can cooperate to accomplish given tasks subject to predefined objectives together as a group. In this research, the predefined objectives are referred to three tasks: (1) to home in towards the RF signal source and then (2) recognize the box and lastly (3) push the box towards wall. Again, such multi-robot solutions would prove highly useful in situations where a single robot is not able to solve the task independently, for example in the clearing of heavy rubble in an accident or disaster site.

In this chapter, the discussions are organized as follow. Firstly, the problem statements are discussed in Section 1.2. Then, the objectives of this research are