University of Exeter
Department of Computer Science

Evolution of Robotic Behaviour Using Gene Expression Programming

Jonathan Mwaura

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

(signature) ....

Publications

Some of the material in chapter 2 has been published in:

> Mwaura, J. and Keedwell, E. (2009). Adative Gene Expression Programming Using a Simple Feedback Heuristic In *Proceedings of the Artificial Intelligence and Simulation of Behaviour(AISB2009)*, Endiburgh, April 2009.

Some of the material in chapter 3 has been published in:

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Abstract

The main objective in automatic robot controller development is to devise mechanisms whereby robot controllers can be developed with less reliance on human developers. One such mechanism is the use of evolutionary algorithms (EAs) to automatically develop robot controllers and occasionally, robot morphology. This area of research is referred to as evolutionary robotics (ER). Through the use of evolutionary techniques such as genetic algorithms (GAs) and genetic programming (GP), ER has shown to be a promising approach through which robust robot controllers can be developed

The standard ER techniques use monolithic evolution to evolve robot behaviour: monolithic evolution involves the use of one chromosome to code for an entire target behaviour. In complex problems, monolithic evolution has been shown to suffer from bootstrap problems; that is, a lack of improvement in fitness due to randomness in the solution set [103, 105, 100, 90]. Thus, approaches to dividing the tasks, such that the main behaviours emerge from the interaction of these simple tasks with the robot environment have been devised. These techniques include the subsumption architecture in behaviour based robotics, incremental learning and more recently the layered learning approach [55, 103, 56, 105, 136, 95]. These new techniques enable ER to develop complex controllers for autonomous robots.

Work presented in this thesis extends the field of evolutionary robotics by introducing Gene Expression Programming (GEP) to the ER field. GEP is a newly developed evolutionary algorithm akin to GA and GP, which has shown great promise in optimisation problems. The presented research shows through experimentation that the unique formulation of GEP genes is sufficient for robot controller representation and development. The obtained results show that GEP is a plausible technique for ER problems. Additionally, it is shown that controllers evolved using GEP algorithm are able to adapt when introduced to new environments.

Further, the capabilities of GEP chromosomes to code for more than one gene have been utilised to show that GEP can be used to evolve manually sub-divided robot behaviours. Additionally, this thesis extends the GEP algorithm by proposing two new evolutionary techniques named multigenic GEP with Linker Evolution (mgGEP-LE) and multigenic GEP with a Regulator Gene (mgGEP-RG). The results obtained from the proposed algorithms show that the new techniques can be used to automatically evolve modularity in robot behaviour. This ability to automate the process of behaviour sub-division and optimisation in a modular chromosome is unique to the GEP formulations discussed, and is an important advance in the development of machines that are able to evolve stratified behavioural architectures with little human intervention.

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Acronyms

Acronym	Meaning
AI	Artificial Intelligence
ADF	Automatically Defined Functions
ANN	Artificial Neural Network
ARL	Adaptive Representation through Learning
AuRA	Autonomous Robot Architecture
BBR	Behaviour Based Robotics
BPGEP	Backtracking Parallel Gene Expression Programming
CGP	Cartesian Genetic Programming
CTRNN	Continuous Time Recurrent Neural Network
EA	Evolutionary Algorithms
EANN	Evolving Artificial Neural Networks
EC	Evolutionary Computation
EP	Evolutionary Programming
ER	Evolutionary Robotics
ES	Evolution Strategies
ET	Expression Tree
FFNN	Feed Forward Neural Network
FLC	Fuzzy Logic Control
GA	Genetic Algorithms
GEP	Gene Expression Programming
GP	Genetic Programming
GRNN	Global Recurrent Neural Network
HGP	Hierarchical Genetic Programming
IAS	Intelligent Autonomous Systems
IFLTE	If Less Than or Equal to
IS	Insertion Sequence Transposition
LGP	Linear Genetic Programming
LISP	LISt Processing
LRNN	Local Recurrent Neural Network
MA	Module Acquisition
MEP	Multi Expression Programming
mgGEP	Multigenic Gene Expression Programming
mgGEP (L)	Multigenic Gene Expression Programming (checking left sensor)
mgGEP - multiple out	Multigenic Gene Expression Programming with multiple output

Acronym	Meaning
mgGEP (OA Priority)	Multigenic Gene Expression Programming (with Obstacle Avoidance as Priority behaviour)
mgGEP-LE	Multigenic Gene Expression Programming with Linker Evolution
mgGEP-RG	Multigenic Gene Expression Programming with Regulator Gene
ORF	Open Reading Frame
RIS	Root Insertion Sequence
SFX	Sensor Fusion Effects
S-R	Stimulus-Response
TGP	Traceless Genetic Programming
ugGEP	Unigenic Gene Expression Programming