

K. Watanabe, M. M. A. Hashem

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Prof. Janusz Kacprzyk
Systems Research Institute
Polish Academy of Sciences
ul. Newelska 6
01-447 Warsaw
Poland
E-mail: kacprzyk@ibspan.waw.pl

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Keigo Watanabe
M. M. A. Hashem

Evolutionary Computations

New Algorithms
and their Applications
to Evolutionary Robots



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Prof. Keigo Watanabe
Saga University
Dept. of Advanced Systems
Control Engineering
Honjomachi 1
840-8502 Saga
Japan
E-mail: watanabe@me.saga-u.ac.jp

Prof. M. M. A. Hashem
Dept. of Computer Science and Engineering
Khulna University of Engineering
and Technology
Khulna 9203, Bangladesh
E-mail: mma_hashem@hotmail.com

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Preface

Evolutionary Computation (EC) is one of the most important emerging technologies of recent times. Over the last ten years there has been exponential growth of research activity in this field. Evolutionary computation has become the standard term that encompasses all of the Evolutionary Algorithms (EAs). The term is still relatively new and represents an effort to bring together different paradigms of EAs and their respective applications. EAs — the unifying term for Genetic Algorithms (GAs), Evolution Strategies (ESs), and Evolutionary Programming (EP) — have received considerable attention to scientists and engineers during last decade. Gleaned from biological metaphors, they are intended to serve as general-purpose easy-to-use optimization techniques capable of reaching globally optimal or at least nearly optimal solutions. This is realized by biologically inspired variation and selection rules. These rules are applied to a population (or several sub-populations) of candidate solutions (individuals) that are evaluated with respect to their fitness. Thus, it is possible by an evolutionary loop to successively approximate the optimal state of the system to be investigated.

Due to their robustness, EAs are well-suited techniques for industrial and management tasks. They do not need gradient information and they can operate on each kind of parameter space (continuous, discrete, combinatorial, or even mixed variants). By means of the population concept, EAs can easily be parallelized. This is why; they often exhibit superior speedup behavior compared to traditional optimization techniques. Essentially, the credibility of evolutionary algorithms relies on their ability to solve difficult, real-world problems with the minimal amount of human effort. If it cannot make the successful transition from academic exercise to industrial application it will be abandoned in favor of other optimizing tools and techniques. The overall goal of this book is to develop and analyze a class of evolutionary algorithms that can be applied to real-world problems of global optimization successfully. Thus the understanding and applications of evolutionary algorithms are clearly extended by this work.

EAs that constitute the evolutionary computation have emerged as the primary unifying principle of modern biological thought for global optimization. Classic Darwinian evolutionary theory, combined with the selectionism of Weismann and the genetics of Mendel, has now become a rather universally accepted set of arguments known as the neo-Darwinian paradigm. Under this paradigm, this book has discussed the development of a new class of evolutionary algorithms and their appli-

cations to robotic control. These algorithmic developments are more closely related to the biological metaphor and natural phenomena with respect to canonical EAs. Specifically, this book is the compilation of our recent research results to this field. The book is aimed at a large audience: graduate students, researchers, engineers, designers — who faces complicated but challenging optimization tasks. In particular, this book will be of interest to the robotic control engineers. An understanding of basic mathematics and concepts of programming is sufficient to follow all presented materials of this book.

The book is organized as follows: In **Chapter 1**, an attempt has been made to overview the basic constituents, similarities and differences, properties, merits and demerits of major evolutionary algorithms in terms of their canonical forms for clear understanding. But in practice the borders between these approaches are much more fluid. Until recently and as that of this book, it is observed a steady evolution in this field by modifying (mutating), (re)combining, and validating (evaluating) the current approaches, permanently improving the population of evolutionary algorithms.

In **Chapter 2**, a new evolutionary algorithm called a novel evolution strategy (NES) has been proposed and tested on various benchmark unconstrained test problems. This algorithm utilized two new genetic operators — stable subpopulation-based max-mean arithmetical crossover (SBMAC) and time-variant mutation (TVM) — which are more closely resembled to natural evolved systems. The effectiveness of this algorithm is compared with other evolutionary algorithm produced results. This preliminary investigation showed that this algorithm could outperform well-established evolutionary algorithms with respect to convergence reliability as well as to solution precision. Consequently, this algorithm showed considerably balance between exploration and exploitation trade-off. Empirical investigations, which are mostly followed by every evolutionary algorithm designer, are also carried out for optimal exogenous parameters of the proposed algorithm.

In **Chapter 3**, a general constraint optimization problem is defined and several methods for constraint-handling by evolutionary algorithms are reviewed. A new log-dynamic penalty function-based fitness function has been developed for the NES algorithm. The characteristics of the NES algorithm have been discussed by emphasizing them towards the constrained optimization. Finally, the effectiveness of the NES algorithm for constrained optimization has been compared with the TPEP and GENOCOP II systems against some complex constrained optimization problems. The performance of the NES algorithm seemed to be an effective method for constrained parameter optimization problems.

In **Chapter 4**, another new evolutionary algorithm called an incest prevented evolution strategy (IPES) by enhancing the novel evolution strategy (**Chapter 2**) has been proposed and tested on various unconstrained test functions. This incest prevented concept was directly related to the natural genetic metaphor. The effectiveness of this algorithm has also been compared with other evolutionary algorithms as well as with novel evolution strategy. The proposed algorithm outperformed other evolutionary algorithms and novel evolution strategy with respect to the evaluation time, solution precision and convergence reliability.

In **Chapter 5**, some optimal control problems have been solved using the NES for which dynamic programming techniques suffer from ill-conditioned dimensionality problem. The NES and the ESs consisting of either conventional crossover method or uniform mutation have also been investigated with different optimization modes. The exogenous parameters of the NES algorithm have been verified in these applications that confirmed the empirical investigated results on test functions that had been conducted in **Chapter 2**. Two discrete-time optimal control problems have been solved evolutionarily with different control steps. In particular, the results were encouraging because the closeness of the evolutionary solutions to analytical ones was perfectly satisfying. The simulation results indicate that the proposed operators in the NES can outperform the conventional ESs with respect to convergence and accuracy of the solutions. An optimal compromise was found between exploration and exploitation in the evolutionary process by the introduction of the proposed operators in the ES.

In **Chapter 6**, a novel optimal controller design technique using the IPES has been developed for mobile robots. A unique fitness function has been constructed based on the direct simulation of different controllers. As opposed to the traditional algebraic Riccati equation solution that requires certain trial and error, these controllers are designed evolutionarily using this unique fitness function. These evolutionarily designed controllers when simulated for the stipulated time, they produced quite satisfactory control responses. Thus, an automatic way was proposed and tested for designing robot controllers in this chapter.

In **Chapter 7**, an ES has been discussed using the statistical information of subgroups. In the method, the subgrouping has been obtained automatically by a similarity metric of individuals at each generation. The arithmetical crossover operation was performed with the elite individual and a mean individual within each subgroup to produce the offspring. The standard deviation calculated within a subgroup has been used in the mutation operation. The proposed ES was applied to the acquisition of a control system for a terminal control problem in an omnidirectional mobile robot, in which the control system of the robot was based on the fuzzy behavior-based control system that combines the concept of subsumption-like architecture and fuzzy reasoning technique.

In **Chapter 8**, a two-phase navigation architecture of intelligent autonomous robots has been proposed to take advantages of local and global planning. For the first phase, an evolutionary technique has been discussed for the collision free optimal trajectory planning of a point mobile robot considering its motions. The formulated problem was composed of a mixed integer and discrete constrained optimization problem. It was really difficult to solve such a problem with the conventional calculus based methods. The obstacles within the environment have been modeled/approximated as circles as well as ellipses from the visibility and sensor modeling concepts to construct a fitness function for the problem. An evolutionary trajectory-planning algorithm based on the NES algorithm has been proposed to solve the problem associated with the first phase of IAR navigation. The proposed algorithm responded well for all the simulation cases. The evolutionary approach

was robust in the sense that it was guaranteed to yield a trajectory terminating at the goal with minimum time and distance while avoiding obstacles.

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Keigo Watanabe
M.M.A. Hashem

Contents

List of Figures	xv
List of Tables	xix
1. Evolutionary Algorithms: Revisited	1
1.1 Introduction	1
1.2 Stochastic Optimization Algorithms	2
1.2.1 Monte Carlo Algorithm	2
1.2.2 Hill Climbing Algorithm	3
1.2.3 Simulated Annealing Algorithm	4
1.2.4 Evolutionary Algorithms	5
1.3 Properties of Stochastic Optimization Algorithms	7
1.4 Variants of Evolutionary Algorithms	8
1.4.1 Genetic Algorithms	8
1.4.2 Evolution Strategies	9
1.4.3 Evolutionary Programming	10
1.4.4 Genetic Programming	10
1.5 Basic Mechanisms of Evolutionary Algorithms	12
1.5.1 Crossover Mechanisms	13
1.5.2 Mutation Mechanisms	14
1.5.3 Selection Mechanisms	15
1.6 Similarities and Differences of Evolutionary Algorithms	17
1.7 Merits and Demerits of Evolutionary Algorithms	17
1.7.1 Merits	17
1.7.2 Demerits	18
1.8 Summary	19
2. A Novel Evolution Strategy Algorithm	21
2.1 Introduction	21
2.2 Development of New Variation Operators	22
2.2.1 Subpopulations-Based Max-mean Arithmetical Crossover ..	22
2.2.2 Time-Variant Mutation	24
2.3 Proposed Novel Evolution Strategy	25
2.3.1 Initial Population	25

2.3.2	Crossover	25
2.3.3	Mutation	25
2.3.4	Evaluation	26
2.3.5	Alternation of Generation	26
2.4	Proposed NES: How Does It Work?	26
2.5	Performance of the Proposed Evolution Strategy	40
2.5.1	Test Functions	41
2.5.2	Implementation and Results	42
2.6	Empirical Investigations for Exogenous Parameters	44
2.6.1	Investigation for Optimal Subpopulation Number	47
2.6.2	Investigation for Optimal Degree of Dependency	49
2.7	Summary	51
3.	Evolutionary Optimization of Constrained Problems	53
3.1	Introduction	53
3.2	Constrained Optimization Problem	53
3.3	Constraint-Handling in Evolutionary Algorithms	55
3.4	Characteristics of the NES Algorithm	57
3.4.1	Characteristics of the SBMAC Operator	57
3.4.2	Characteristics of the TVM Operator	58
3.4.3	Effects of the Elitist Selection	58
3.5	Construction of the Constrained Fitness Function	58
3.6	Test Problems	60
3.7	Implementation, Results and Discussions	61
3.7.1	Implementation	61
3.7.2	Results and Discussions	61
3.8	Summary	63
4.	An Incest Prevented Evolution Strategy Algorithm	65
4.1	Introduction	65
4.2	Incest Prevention: A Natural Phenomena	66
4.3	Proposed Incest Prevented Evolution Strategy	66
4.3.1	Impact of Incest Effect on Variation Operators	66
4.3.2	Population Diversity and Similarity	67
4.3.3	Incest Prevention Method	67
4.4	Performance of the Proposed Incest Prevented Evolution Strategy ..	68
4.4.1	Case I: Test Functions for Comparison with GA, EP, ESs and NES	68
4.4.2	Case II: Test Functions for Comparison Between the NES and IPES Algorithms	69
4.5	Implementation and Experimental Results	70
4.5.1	Case I: Implementation and Results	70
4.5.2	Case II: Implementation and Results	73
4.6	Summary	75

5. Evolutionary Solution of Optimal Control Problems	77
5.1 Introduction	77
5.2 Conventional Variation Operators	78
5.2.1 Arithmetical Crossover/Intermediate Crossover	78
5.2.2 Uniform Mutation	78
5.3 Optimal Control Problems	78
5.3.1 Linear-Quadratic Control Problem	79
5.3.2 Push-Cart Control Problem	79
5.4 Simulation Examples	80
5.4.1 Simulation Example I: ESs with TVM and UM Operators	80
5.4.2 Simulation Example II: ESs with SBMAC and Conventional Methods	80
5.4.3 Implementation Details	81
5.5 Results and Discussions	81
5.5.1 Results for Example I	82
5.5.2 Results for Example II	84
5.5.3 Results from the Evolutionary Solution	84
5.6 Summary	87
6. Evolutionary Design of Robot Controllers	89
6.1 Introduction	89
6.2 A Mobile Robot with Two Independent Driving Wheels	89
6.3 Optimal Servocontroller Design for the Robot	91
6.3.1 Type-1 Optimal Servocontroller Design	91
6.3.2 Type-2 Optimal Servocontroller Design	93
6.4 Construction of the Fitness Function for the Controllers	94
6.4.1 Basic Notion	94
6.4.2 Method	95
6.5 Considerations for Design and Simulations	96
6.6 Results and Discussions	97
6.6.1 Design Results for Type-1 Controller	97
6.6.2 Design Results for Type-2 Controller	98
6.7 Summary	100
7. Evolutionary Behavior-Based Control of Mobile Robots	103
7.1 Introduction	103
7.2 An Evolution Strategy Using Statistical Information of Subgroups	103
7.2.1 Group Division	103
7.2.2 Max-mean Arithmetical Crossover	104
7.2.3 Mutation with Directly Calculated Standard Deviation	105
7.3 Omnidirectional Mobile Robot	105
7.3.1 Dynamical Mode of the Robot	105
7.3.2 Jacobian Matrix	107
7.4 Fuzzy Behavior-Based Control System	107
7.5 Acquisition of Control System	109

7.5.1	Parameter Setting	109
7.5.2	Learning Result	110
7.6	Summary	111
8.	Evolutionary Trajectory Planning of Autonomous Robots	113
8.1	Introduction	113
8.2	Fundamentals of Evolutionary Trajectory Planning	113
8.3	Formulation of the Problem for Trajectory Planning	115
8.4	Polygonal Obstacle Sensing and Its Representation	117
8.4.1	Obstacle Sensing and Representation as Circles	117
8.4.2	Some Practical Considerations	118
8.5	Special Representations of Evolutionary Components	120
8.5.1	Representation of Individuals	121
8.5.2	Representation of SBMAC	121
8.5.3	Representations of Additional Operators	123
8.6	Construction of the Fitness Function	124
8.7	Bounds for Evolutionary Parameters	125
8.7.1	Bounds for Terminal Sampling Instant	126
8.7.2	Bounds for Steering Angle	127
8.8	Proposed Evolutionary Trajectory Planning Algorithm	129
8.9	Considerations and Simulations	131
8.9.1	Simulation Example I: Local Trajectory Planning	131
8.9.2	Simulation Example II: Global Trajectory Planning	132
8.10	Results and Discussions	134
8.11	Summary	136
A.	Definitions from Probability Theory and Statistics	139
A.1	Random Variables, Distributions and Density Functions	139
A.2	Characteristics Values of Probability Distributions	139
A.2.1	One Dimensional Distributions:	139
A.2.2	Multidimensional Distributions	140
A.3	Special Distributions	140
A.3.1	The Normal or Gaussian Distribution	140
A.3.2	The n -Dimensional Normal Distribution	141
A.3.3	The χ^2 Distribution	142
A.3.4	The Cauchy Distribution	142
B.	C-Language Source Code of the NES Algorithm	143
C.	Convergence Behavior of Evolution Strategies	155
C.1	Convergence Reliability	155
C.2	Convergence Velocity	157
	References	159
	Index	169

List of Figures

1.1	A pseudo-code structure of the Monte Carlo algorithm	3
1.2	A pseudo-code structure of the Hill Climbing algorithm	3
1.3	A pseudo-code structure of the Simulated Annealing algorithm	4
1.4	An abstract view of the simulated evolutionary search cycle for global optimization	6
1.5	A pseudo-code structure of evolutionary algorithms	6
1.6	Parse tree representation of the computer program (symbolic expression) that computes a root of the quadratic equation $ax^2 + bx + c$, expressed by $((/ (+ (- 0 b) (\text{sqrt} (- (* b b) (* 4 (* a c))))) (* 2 a))$. .	11
2.1	An example of the subpopulation-based max-mean arithmetical crossover	23
2.2	The characteristics of $\sigma(t)$ with $\gamma = 6.0$ and $T = 200$	25
2.3	A pseudo-code structure of the proposed evolution strategy	26
2.4	Three-dimensional view and contour plots of the sphere model (f_2) function	42
2.5	Three-dimensional view and contour plots of the step (discontinuous) (f_3) function	43
2.6	Three-dimensional view and contour plots of the multimodal (Ackley) (f_9) function	43
2.7	The Evolution history of the proposed algorithm for the function \tilde{f}_2	44
2.8	The Evolution history of the proposed algorithm for the function f_3	44
2.9	The Evolution history of the proposed algorithm for the function f_9	46
2.10	Three-dimensional view and contour plots of the six-hump camel back function	47
2.11	Three-dimensional view and contour plots of the Bohachevsky function #1	48
2.12	The effect of selection of different subpopulations on the six-hump camel back function	48
2.13	The effect of selection of different subpopulations on the Goldstein-Price function	49
2.14	The effect of selection of different subpopulations on the Bohachevsky #1 function	50
2.15	The effect of selection of different γ values on the six-hump camel back function	50
2.16	The effect of selection of different γ values on the Goldstein-Price function	51

2.17	The effect of selection of different γ values on the Bohachevsky #1 function	51
3.1	A typical two-dimensional search space $\mathcal{S} \subseteq R^2$ and its feasible \mathcal{F} and infeasible \mathcal{U} parts	54
3.2	An evolution history of the algorithm for the <i>Problem 1</i>	63
3.3	An evolution history of the algorithm for the <i>Problem 4</i>	64
4.1	A pseudo-code structure of the proposed incest prevented evolution strategy	68
4.2	Inverted three dimensional view and contour plots of the $F2$ function ...	70
4.3	Three dimensional view and contour plots of the $F3$ function	71
4.4	Three dimensional view and contour plots of the $F8$ function	71
4.5	Three dimensional view and contour plots of the $F9$ function	72
4.6	Comparison of the evolution histories of the NES and IPES algorithms for the function \tilde{f}_2	73
4.7	Comparison of the evolution histories of the NES and IPES algorithms for the function f_3	73
4.8	Comparison of the evolution histories of the NES and IPES algorithms for the function f_9	74
5.1	The evolution histories of the LQC problem with control steps, $N = 15$.	82
5.2	The evolution histories of the LQC problem with control steps, $N = 20$.	82
5.3	The evolution histories of the PCC problem with control steps, $N = 10$.	83
5.4	The evolution histories of the PCC problem with control steps, $N = 20$.	83
5.5	The evolution histories of the LQC problem with control steps, $N = 5$ and $\gamma = 8.0$	84
5.6	The evolution histories of the LQC problem with control steps, $N = 20$ and $\gamma = 8.0$	85
5.7	The evolution histories of the PCC problem with control steps, $N = 15$ and $\gamma = 8.0$	85
5.8	The evolution histories of the PCC problem with control steps, $N = 20$ and $\gamma = 8.0$	87
6.1	A mobile robot with two independent driving wheels	90
6.2	Type-1 optimal servocontroller for the mobile robot	93
6.3	Type-2 optimal servocontroller for the mobile robot	95
6.4	The evolution histories for type-2 controller simulation	97
6.5	The population diversity histories for type-2 controller simulation	98
6.6	Velocity control response from type-1 controller	99
6.7	Azimuth control response from type-1 controller	99
6.8	Straight line trajectory control response from type-1 controller	100
6.9	Velocity control responses from type-2 controller	100
6.10	Azimuth control response from type-2 controller	101
6.11	Circular trajectory control response from type-2 controller	101

7.1	Evolution strategy using statistical information of subgroup	104
7.2	Model of an omnidirectional mobile robot	106
7.3	Behavior model for an omnidirectional mobile robot	108
7.4	Fuzzy behavior-based control system	109
7.5	Structure of individual	110
7.6	Resulting mobile robot path	110
7.7	Resulting rotational angle of robot	111
7.8	History of minimum value of fitness	111
8.1	A simplified two-phase architecture for an intelligent autonomous robot navigation	114
8.2	A two-dimensional world model in which a point mobile robot is traveling among polygonal obstacles	115
8.3	A polygonal obstacle \mathcal{O}_i is enclosed by a circle \mathcal{C}_i	118
8.4	An example of a polygonal obstacle \mathcal{O}_i is enclosed by an ellipse \mathcal{E}_i (a) by an ordinary ellipse, (b) by an 4-ellipse	119
8.5	A circular robot is moving among the expanded circular modeled obstacles	120
8.6	The SBMAC operation with variable length individuals for the case (1)	122
8.7	The SBMAC operation with variable length individuals for the case (2)	122
8.8	An instance of (a) before swapping crossover operation, and (b) after swapping crossover operation	123
8.9	An example of (a) insertion mutation, and (b) deletion mutation for an instance	124
8.10	Possible directions of the robot's motion among the obstacles and selection of the N bounds	127
8.11	An example for setting up θ_u and θ_l where $\beta > \alpha_2$	127
8.12	An example for setting up θ_u and θ_l where $\beta < \alpha_2$	129
8.13	A division of the range $[-\pi, \pi]$ into four quadrants	129
8.14	The optimal trajectory of the robot for <i>Case I</i> of local trajectory planning	133
8.15	The optimal trajectory of the robot for <i>Case II</i> of local trajectory planning	133
8.16	The optimal trajectories of the robot for <i>Case A</i> of global trajectory planning	135
8.17	The optimal trajectories of the robot for <i>Case B</i> of global trajectory planning	136
8.18	The evolution history of the algorithm for a simulation example	136

List of Tables

1.1	Main characteristics of evolutionary algorithms	18
2.1	Performance comparison of the proposed evolution strategy with evolution strategies, evolutionary programming and genetic algorithm for the test functions \tilde{f}_2 , f_3 and f_9	45
3.1	Performance comparison of the novel evolution strategy algorithm with the TPEP and GENOCOP II systems for constrained optimization	62
4.1	The test functions which have been selected to evaluate the relative performances of the proposed incest prevented evolution strategy and novel evolution strategy	69
4.2	Performance comparison of the proposed incest prevented evolution strategy for the test functions \tilde{f}_2 , f_3 and f_9 with evolution strategies, evolutionary programming, genetic algorithm and novel evolution strategy	74
4.3	Relative performance comparison between the proposed incest prevented evolution strategy and novel evolution strategy for the test functions $F1$ to $F9$	75
8.1	Circular approximated polygonal obstacle sizes and position coordinates within the environment 1	132
8.2	Circular and elliptically approximated polygonal obstacle sizes and position coordinates within the environment 2	132
8.3	Local trajectory planning parameters for <i>Case I</i> of the environment 1 . . .	133
8.4	Local trajectory planning parameters for <i>Case II</i> of the environment 1 . . .	134
8.5	Global trajectory planning parameters for <i>Case A</i> of the environment 1 . .	134
8.6	Global trajectory planning parameters for <i>Case B</i> of the environment 2 . .	135