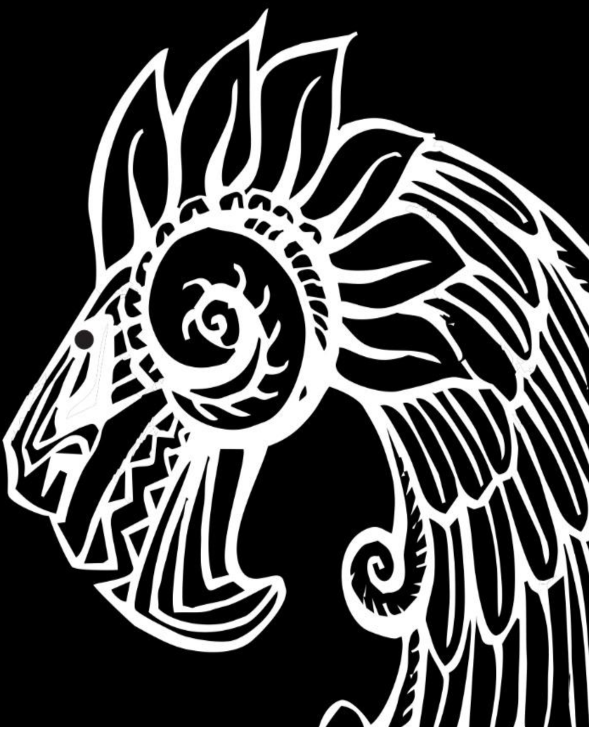
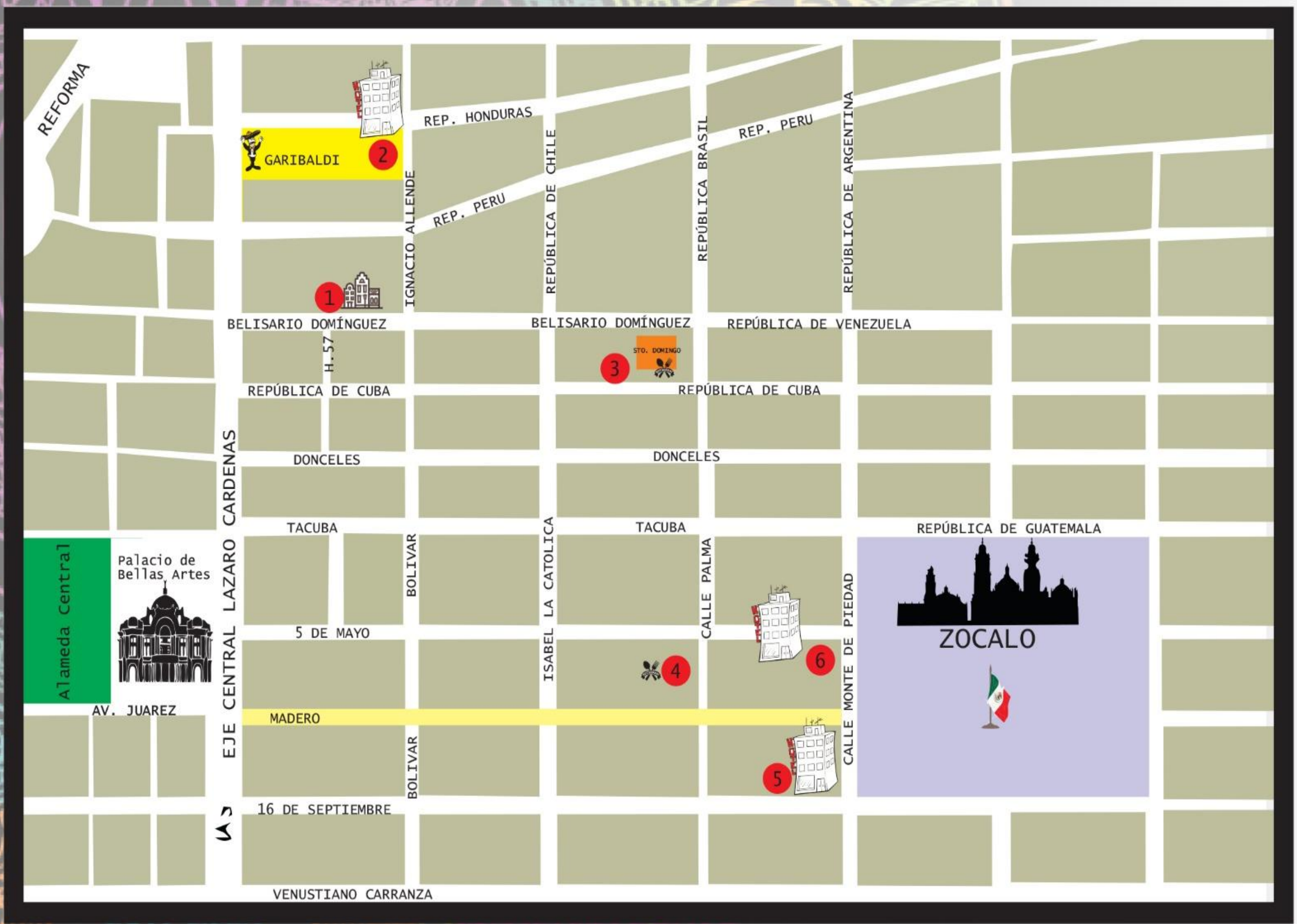
NEO

2018 CD**MX**



6th International Workshop on
Numerical and Evolutionary Optimization
September 26 - 28, 2018
http://neo.cinvestav.mx



1.- **Centro de Educación Continua Ing. Eugenio Méndez Docurro.**
Belisario Domínguez #22 (Venue).

2.- **Hotel MX Garibaldi.**
Repúbliaca de Honduras #11.

3.- **Restaurante Domingo Santo Boutique**
República de Cuba #96.

4.- **Restaurante El Cardenal**
Palma #23.

5.- **Gran Hotel Ciudad de México**
16 de Septiembre #82.

6.- **Best Western Hotel Majestic**
Francisco I. Madero #73. (Gala Dinner).

Contents

Additional Information

Foreword

Welcome

Welcome to NEO 2018, the 6th International Workshop on Numerical and Evolutionary Optimization. In this edition, NEO 2018 occurs from September 26 to 28, 2018. Hosting the workshop this year is the Instituto Politécnico Nacional (IPN), an institution with more than 80 years making innovation and professional education in science and technology in Mexico. The workshop will take place at Centro de Educación Contínua del IPN (CEC) "Eugenio Mendez Docurro" which is in the historical center of Mexico City, CdMx, México.

The goal of the Numerical and Evolutionary Optimization (NEO) workshop series is to bring together people from these and related fields to discuss, compare and merge their complementary perspectives. NEO encourages the development of fast and reliable hybrid methods, that maximize the strengths and minimize the weaknesses of each underlying paradigm; while also applying to a broader class of problems. Moreover, NEO fosters the understanding and adequate treatment of real-world problems, particularly in emerging fields that affect us all such as healthcare, smart cities, big data, among many others.

In this 2018 edition, there will be more than 80 participants coming from all over Mexico. The NEO 2018 will have more than 50 technical presentations addressing different optimization subjects and dealing with a variety of challenging applications. Finally, it is worth to notice that over the years, the NEO community has grown not only in number but also concerning gender diversity. This year we arrange, for the first time in this conference series, a special session called Women at NEO (W-NEO) as an effort to make more visible the work in optimization performed by our female pairs. We hope you enjoy your participation at the NEO 2018, thank you for your valuable assistance.

Sincerely,
Dr. Adriana Lara, ESFM-IPN
Dr. Oliver Schuetze, Cinvestav-IPN
NEO 2018 General Chairs

Acknowledgments

We want to thank all participants that helped to make the NEO 2018 such a great success. In particular, we would like to thank Keynote Speakers: Kalyanmoy Deb (Michigan State University, USA), Juan-Qiao Sun (UC Merced, USA), Manuel Bogoya (Pontificia Universidad Javeriana, Colombia), and Carlos Hernandez (Mutuo Financiera, Mexico) and Tutorial Speaker Carlos A. Coello Coello (Cinvestav-IPN, Mexico) as well as the Session Chairs for the sessions Discrete Optimization: Marcela Quiroz (UV Xalapa); Optimization for Digital Analysis and Processing: Javier Flavio Vigueras Gómez, Aldo Rodrigo Mejía Rodríguez, Guadalupe Dorantes Méndez (U.A.S.L.P) and Jean-Bernard Hayet (CIMAT); Set-Oriented Numerics: Carlos Hernandez (Mutuo Financiera) and Women at NEO: Marta Cabo (ITAM), América Morales(CINVESTAV), Laura Cruz (ITCM), Marcela Quiroz (UV) and Yazmin Maldonado (ITT). Also to Laura Muñoz (ESCOM-IPN) for her support to recruit interested students. Further, we gratefully acknowledge financial support from the Basic Science Group Project No. 285599, from the publisher MDPI, from our institutions, ESFM-IPN and Cinvestav-IPN, and the CEC-IPN Eugenio Mendez to give us the opportunity to hold the workshop in this lovely place. Finally, we would like to thank all the persons without whom the NEO 2018 would not have been made possible: the staff members Felipa Rosas, Erika Rios, Sofy Reza, Jose Luis Flores, Santiago Dominguez, and Arcadio Morales From the Cinvestav-IPN. Miguel Tufiño and Adriana Plascencia from ESFM-IPN. Also from students Fernanda Beltran (Cinvestav-IPN), and very specially to Lourdes Uribe (ESFM-IPN) and Oliver Cuate (Cinvestav-IPN). We would like to express our special thanks to Impakt 45 S.A. de C.V. who made an amazing job to make all the arrangements for the NEO 2018.

Partners

Schedule

NEO 2018

Speakers

Speaker	Sesion ID	Day	Hour	Room
Adriana Lara López	W-NEO	sept. 26	11:30-13:00	NEO 2
Alberto Rodríguez Sánchez	MOO I	sept. 26	12:00-12:30	Aula 1
América Morales	ROB	sept. 27	16:45-17:15	NEO 2
América Morales	W-NEO	sept. 26	11:30-13:00	NEO 2
Ángel David Téllez Macías	DO II	sept. 28	10:30-11:00	Aula 1
C. Nuñez-Perez	ODAP I	sept. 27	12:30-13:00	Aula 1
Carlos Coello Coello	Tutorial	sept. 26	16:45-18:15	Aula 1
Carlos Hernández	MOO III	sept. 27	11:30-12:30	Aula 1
Christian Noguez Moreno	MOO VI	sept. 28	11:15-11:45	Aula 1
Christian Noguez Moreno	W-NEO	sept. 26	11:30-13:00	NEO 2
Claudia Gómez-Santillan	DO II	sept. 28	10:00-10:30	Aula 1
Claudia Gómez-Santillan	W-NEO	sept. 26	11:30-13:00	NEO 2
Claudia Orquidea López	DO I	sept. 26	16:45-17:15	NEO 2
Claudia Orquidea López	W-NEO	sept. 26	11:30-13:00	NEO 2
Darian Reyes Fernández	MOO III	sept. 27	12:30-13:00	Aula 1
David Laredo	AN	sept. 27	09:00-09:30	NEO 2
Esteban Gamboa García	MOO I	sept. 26	12:30-13:00	Aula 1
Guillermo Morales Luna	Cinvestav	sept. 26	14:00-15:00	Aula 1
Heriberto Cruz Hernández	ODAP I	sept. 27	11:30-12:00	NEO 2
Isaac López López	DO I	sept. 26	17:45-18:00	NEO 2
J.N Martínez-Castelán	DE	sept. 26	15:00-15:30	Aula 1
J.S Pantoja-García	DE	sept. 26	15:30-16:00	Aula 1
Javier Flavio Vigueras Gomez	ODAP II	sept. 27	15:30-16:00	NEO 2
Javier Gurrola-Ramos	SON	sept. 28	09:30-10:00	NEO 2
Jian-Qiao Sun	Key-Note	sept. 27	10:15-11:15	Aula 1
Jesus Fernández	IND	sept. 26	17:45-18:15	NEO 3
Juan Ceballos Corral	IND	sept. 26	16:45-17:15	NEO 3
Kalyanmoy Deb	Key-Note	sept. 26	10:00-10:15	Aula 1
L.A. Quezada-Téllez	MOO I	sept. 26	11:30-12:00	Aula 1
Laura Cruz Reyes	MOO V	sept. 27	16:45-17:15	Aula 1

Speakers

Speaker	Sesion ID	Day	Hour	Room
Laura Cruz Reyes	W-NEO	sept. 26	11:30-13:00	NEO 2
León Dozal	GP	sept. 26	15:00-15:30	NEO 2
Lourdes Uribe	MOO II	sept. 27	09:30-10:00	Aula 1
Lourdes Uribe	SON	sept. 28	10:00-10:30	NEO 2
Lourdes Uribe	W-NEO	sept. 26	11:30-13:00	NEO 2
Luis Carlos González	GP	sept. 26	16:00-16:30	NEO 2
Luis Muñoz	AN	sept. 27	09:30-10:00	NEO 2
Manuel Bogoya	Key-Note	sept. 27	14:30-15:30	Aula 1
Marta Cabo	DO I	sept. 26	17:15-17:45	NEO 2
Marta Cabo	W-NEO	sept. 26	11:30-13:00	NEO 2
Miriam Pescador	MOO VI	sept. 28	11:45-12:15	Aula 1
Miriam Pescador	W-NEO	sept. 26	11:30-13:00	NEO 2
Mercedes Pérez-Villafuerte	W-NEO	sept. 26	11:30-13:00	NEO 2
Nelson Rangel-Valdez	DO II	sept. 28	09:30-10:00	Aula 1
Oliver Cuate	MOO IV	sept. 27	15:30-16:00	Aula 1
Oliver Cuate	MOO V	sept. 27	16:15-16:45	Aula 1
Oliver Schütze	MOO II	sept. 27	09:00-09:30	Aula 1
Oliver Schütze	Key-Note	sept. 26	09:20-10:00	Aula 1
Perla Juárez	GP	sept. 26	15:30-16:00	NEO 2
Perla Juárez	W-NEO	sept. 26	11:30-13:00	NEO 2
Roides Javier Cruz Lara	DE	sept. 26	16:00-16:30	Aula 1
Saúl Martínez Díaz	ODAP I	sept. 27	12:00-12:30	NEO 2
Saúl Zapotecas-Martínez	SON	sept. 28	10:30-11:00	NEO 2
Sergio Luis Pérez Pérez	IND	sept. 26	17:15-17:45	NEO 3
Teodoro Alvarez-Sánchez	ODAP II	sept. 27	14:30-15:00	NEO 2
Teodoro Alvarez-Sánchez	ODAP II	sept. 27	15:00-15:30	NEO 2
Victor López-López	ROB	sept. 27	16:15-16:45	NEO 2

NEO 2018

Wednesday Sept., 26

<table>
<tr><th colspan="7">Main Room (Aula 1)</th></tr>
<tr><td>9:00 AM</td><td colspan="6">Opening Ceremony</td></tr>
<tr><td>9:20 AM</td><td colspan="5">On Continuation Methods for Continuous MOPs</td><td>by Oliver Schütze</td></tr>
<tr><td>10:00 AM</td><td colspan="6">Coffee Break</td></tr>
<tr><td>10:15 AM</td><td colspan="5">Extreme-Scale Evolutionary Optimization: A Case Study on a Billion-Variable Resource Allocation Problem</td><td>by Kalyanmoy Deb</td></tr>
<tr><td>11:15 AM</td><td colspan="6">Workshop Photo</td></tr>
<tr><td rowspan="4">11:30 AM</td><td>W-NEO Chair: A. Lara</td><td colspan="4">Multi-objective Optimization I (MOO I)</td><td>Chair: Carlos Hernández</td></tr>
<tr><td rowspan="3">room NEO_R2</td><td colspan="4">Multiobjective Optimization of an Investment Portfolio: A Preliminary Study of the American, European, and Mexican Stock Markets</td><td>by Quezada-Téllez L.A.</td></tr>
<tr><td colspan="4">Using a Parallel Tabu Search to Approximate Uniform Design</td><td>by Rodríguez Sánchez Alberto</td></tr>
<tr><td colspan="4">On the Deployment of Radio Frequency Identification Readers: A Multiobjective Perspective</td><td>By Esteban Gamboa García</td></tr>
<tr><td>1:00 PM</td><td colspan="3">Lunch for invited students (at CEC, Jardín Botánico)</td><td colspan="3" rowspan="2">Lunch for the rest of attendees (on your own)</td></tr>
<tr><td>2:00 PM</td><td colspan="2">Studies at CINVESTAV</td><td>by Guillermo Morales</td></tr>
<tr><td></td><td colspan="2">Differential Evolution I</td><td>Chair: Miriam Pescador</td><td colspan="3">Genetic Programming I</td></tr>
<tr><td>3:00 PM</td><td colspan="2">Concurrent Design of a Passive Bipedal Walker using Differential Evolution Algorithm</td><td>by Martínez-Castelán J.N</td><td colspan="3" rowspan="3">room NEO_R2</td></tr>
<tr><td>3:30 PM</td><td colspan="2">Concurrent Design of a Bipedal Lower-limb by Using Differential Evolution</td><td>by Pantoja-García J.S</td></tr>
<tr><td>4:00 PM</td><td colspan="2">Engineering Optimization by Combining an Adapted Nelder-Mead Method with Differential Evolution</td><td>by Roides Javier Cruz Lara</td></tr>
<tr><td>4:30 PM</td><td colspan="6">Coffee Break</td></tr>
<tr><td rowspan="2">4:45 PM</td><td colspan="2">Tutorial</td><td>Chair: Adriana Lara</td><td colspan="2">Discrete Optimization I</td><td>Industrial Applications</td></tr>
<tr><td colspan="2">Metaheurísticas Bio-Inspiradas: Resolviendo problemas como la naturaleza lo haría</td><td>by Carlos A. Coello Coello</td><td colspan="2">room NEO_R2</td><td>room NEO_R3</td></tr>
<tr><td>6:15 PM</td><td colspan="6">End of first day</td></tr>
</table>

Wednesday Sept., 26

Room (NEO_R2)

Time	W-NEO		Multi-objective Optimization I (MOO I)
11:30 AM	Networking time	by Adriana Lara López	Aula 1
1:00 PM	*Lunch*		

Time	Differential Evolution I	Genetic Programming I	Chair: Leonardo Trujillo
3:00 PM	Aula 1	Analysis of Similarity Measures of Protein Sequences Applied to Trees in Genetic Programming	by León Dozal
3:30 PM		Pool-based Genetic Programming with Speciation, Bloat Control and Local Search	by Juárez Perla W-NEO
4:00 PM		Yet Another Guiding Scheme for Multi Objective Evolutionary Algorithms as produced by Genetic Programming	by Luis Carlos González
4:30 PM	*Coffee Break*		

Time	Tutorial	Discrete Optimization I	Chair: Marcela Quiroz	Industrial Applications
4:45 PM	Aula 1	Packing Problem as a Mixed Integer Non-linear Model Using Formulation Space Search	by Claudia Orquidea López W-NEO	room NEO_R3
5:15 PM		Beam Search: A Tree Search Heuristic and its Applications to Cutting and Packing Problems	by Marta Cabo W-NEO	
5:45 PM		Metaheuristics in the Optimization of Cryptographic Boolean Functions	by Isaac López López	

Wednesday Sept., 26

Room (NEO_R3)

Time	W-NEO	Multi-objective Optimization I (MOO I)
11:30 AM	room NEO_R2	Aula 1
1:00 PM	*Lunch*	

Time	Differential Evolution I	Genetic Programming I
3:00 PM	Aula 1	room NEO_R2
4:30 PM	*Coffee Break*	

Time	Tutorial	Discrete Optimization I	Industrial Applications	Chair: Leonardo Trujillo
4:45 PM	Aula 1	room NEO_R2	Multi-Objective Integer Linear Optimization of a Distribution Problem of Brand-New Tractor Units	by Juan Ceballos Corral
5:15 PM			Analysis of Dimensionwise Variation Heuristics for the Multidimensional Assignment Problem	by Pérez Pérez Sergio Luis
5:45 PM			Many-objective Portfolio Optimization for Natural Gas Loans	by Jesus Fernández

NEO 2018

Thursday Sept., 27

Main Room (Aula 1)

Time	Main Room (Aula 1)		
	Multi-objective Optimization II (MOO II) Chair: Marcela Quiroz		Artificial Networks
9:00 AM	On the Design of Hybrid Evolutionary Multi-objetive OptimizationAlgorithms for Constrained MOPs	by Oliver Schütze	Room NEO_2
9:30 AM	An Overview of Constraint Handling Methods for MOPs	by Lourdes Uribe W-NEO	
10:00 AM	*Coffee Break*		
10:15 AM	Cell Mapping Methods - Algorithmic Approaches and Application		by Jian-Qiao Sun
11:15 AM	*Coffee Break*		
	Multi-objective Optimization III (MOO III) Chair: Oliver Schütze		Digital and Analysis Processing (ODAP I)
11:30 AM	Cell Mapping Methods for Multi-objective Optimization	by Carlos Hernández	Room NEO_2
12:30 PM	VHDL by MOEA: a Tool for Multi-objective Optimization in High-Level Synthesis	by Darian Reyes Fernández	
1:00 PM	*Lunch (on your own)*		
	Multi-objective Optimization IV (MOO IV) Chair: Oliver Schütze		Digital and Analysis Processing (ODAP II)
2:30 PM	A Generalization of the Averaged Hausdorff Distance Δp	by Manuel Bogoya	Room NEO_2
3:30 PM	Using the Pareto Explorer Framework for the Decision-making Processes in Real-world Applications	by Oliver Cuate	
4:00 PM	*Coffee Break*		
	Multi-objective Optimization V (MOO V) Chair: Saúl Zapotecas		Robotics
4:15 PM	Variation Rate: an Alternative to Maintain Diversity in Decision Space for Multi-objective Evolutionary Algorithms	by Oliver Cuate	Room NEO_2
4:45 PM	DPEM-HH: A population Evolvability-based Multi-objective Hyperheuristic to Solve Dynamic Multi-objective Optimization Problems	by Lara Cruz W-NEO	
5:15 PM	*End of talks*		
6:30 PM 12:00 AM	*GALA DINNER*		

Thursday Sept., 27

Room NEO_2

	Artificial Networks — Chair: Yazmín Maldonado		Multi-objective Optimization II (MOO II)
9:00 AM	A Neural Network-Evolutionary Computation Framework for Remaining Useful Life Estimation	by David Laredo	Aula 1
9:30 AM	Transfer Learning of Evolved Feature Transformations	by Luis Muñoz	
10:00 AM	*Coffee Break*		
10:15 AM	Key-note talk in Aula 1		
11:15 AM	*Coffee Break*		
	Digital and Analysis Processing (ODAP I) — Chair : F. Javier Vigueras		Multi-objective Optimization III (MOO III)
11:30 AM	A Method to Optimize the Order Type Maximal Perturbation Through Multiple Single Point Displacements	by Heriberto Cruz Hernández	Aula 1
12:00 PM	Depth Estimation for a Monocular Vision System	by Martínez Díaz Saúl	
12:30 PM	Dynamical and Numerical Analysis of Chen Chaotic Oscillator	by Nuñez-Perez C	
1:00 PM	*Lunch (on your own)*		
	Digital and Analysis Processing (ODAP II) — Chair: F. Javier Vigueras		Multi-objective Optimization IV (MOO IV)
2:30 PM	Implementation Of An Object Recognition System Based On Deep Learning In A Rpas	by Teodoro Alvarez-Sánchez	Aula 1
	Real-Time Weapon Recognition Using Deep Learning	by Teodoro Alvarez-Sanchez	
3:30 PM	Probabilistic Uniformity as a Similarity Measure Robust to Lighting Changes	by Javier Flavio Vigueras Gomez	
4:00 PM	*Coffee Break*		
	Robotics — Chair: Adriana Lara		Multi-objective Optimization V (MOO V)
4:15 PM	Improving a Vision-based SLAM System Using Novelty Search	by Victor López-López	Room NEO_2
4:45 PM	A Review in Autonomous Driving: present and future trends	by America Morales W-NEO	
5:15 PM	*End of talks*		
6:30 PM	*GALA DINNER*		
12:00 AM			

NEO 2018

Friday Sept, 28

Main Room (Aula 1)

	Discrete Optimization II (DO II) Chair : Marcela Quiroz		Set Oriented Numerics (SON)
9:30 AM	A study of the Effect of the Decision Maker Profile in the Decision-making Process	by Nelson Rangel	Room NEO_2
10:00 AM	Obtaining Inference Rules Through Compensatory Fuzzy Logic for Decision Problems with Imperfect Knowledge	by Gómez-Santillan Claudia W-NEO	
10:30 AM	Multi-objective Optimization of the Supply Chain Design and Operation	by Angel David Téllez Macías	
11:00 AM	*Coffee Break*		
	Multi-objective Optimization VI (MOO VI) Chair: Adriana Lara		
11:15 AM	Efficiency of Mexican Universities Using Minimum Distance Approach in Data Envelopment Analysis	by Christian Lizbeth Noguez Moreno W-NEO	
11:45 AM	Automatic Design of Multiobjective Optimization Evolutionary Algorithm Based on Decomposition	by Miriam Pescador W-NEO	
12:15 PM	*CLOSING SESSION*		
	End of Workshop		

Room NEO_2

	Set Oriented Numerics (SON) Chair: Carlos Hernández		Discrete Optimization II (DO II)
9:30 AM	COLSHADE-Levy for Constrained Optimization	by Javier Gurrola-Ramos	Aula 1
10:00 AM	The Δp Newton Method	by Lourdes Uribe W-NEO	
10:30 AM	On the Stability in Dynamic Systems to Analyze Evolutionary Multiobjective Algorithms	by Saúl Zapotecas-Martínez	
11:00 AM	*Coffee Break*		
	Multi-objective Optimization VI (MOO VI)		
11:15 AM 11:45 AM	Aula 1		
12:15 PM	*CLOSING SESSION*		
	End of Workshop		

II Invited Speakers

Kalyanmoy Deb

Extreme-Scale Evolutionary Optimization: A Case Study on a Billion-Variable Resource Allocation Problem

Michigan State University, USA

Talk Abstract

Optimization methods and practices are around for more than 50 years, but they are still criticized for their "curse of dimensionality". In this talk, we shall look at a specific large-dimensional integer-valued resource allocation problem class from practice and review the performance of well-known softwares, such as IBM's CPLEX, on the problem. Thereafter, we shall present a population-based heuristic search algorithm that has the ability to recombine short-sized building blocks, despite having overlapping variable linkage, to form larger-sized building blocks. The process is eventually able to solve a billion-variable version of the problem to near-optimality in a polynomial computational time, making the application one of the largest size optimization problems ever solved.

Short Biography

Kalyanmoy Deb is Koenig Endowed Chair Professor at Department of Electrical and Computer Engineering in Michigan State University, USA. Prof. Deb's research interests are in evolutionary optimization and their application in multi-criterion optimization, modeling, and machine learning. He has worked at various universities across the world including IITs in India, University of Dortmund and Karlsruhe Institute of Technology in Germany, Aalto University in Finland, University of Skovde in Sweden, Nanyang Technological University in Singapore. He was awarded Infosys Prize, TWAS Prize in Engineering Sciences, CajAstur Mamdani Prize, Distinguished Alumni Award from IIT Kharagpur, Edgeworth-Pareto award, Bhatnagar Prize in Engineering Sciences, and Bessel Research award from Germany. He has been awarded IEEE CIS's "EC Pioneer Award". He is fellow of IEEE, ASME, and three Indian science and engineering academies. He has published over 490 research papers with Google Scholar citation of over 116,000 with h-index 110. He is in the editorial board on 18 major international journals. More information about his research contribution can be found from http://www.egr.msu.edu/ kdeb.

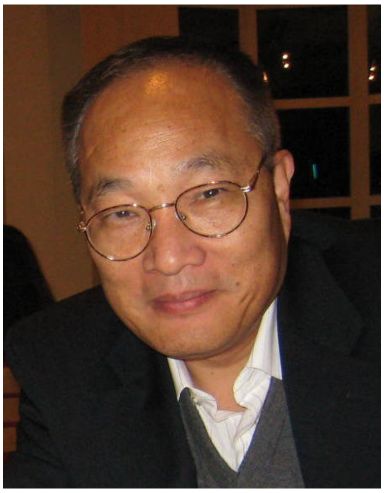
Jian-Qiao Sun

Cell Mapping Methods - Algorithmic Approaches and Application

University of California, Merced, USA

Talk Abstract

Research collaborations of University of California at Merced, CINVESTAV-IPN in Mexico and Tianjin University in China have advanced the study of multi-objective optimization problems, and resulted in a recent publication of a book printed by Springer. This talk presents an overview of the book and a summary of the research advances. In particular, we first discuss several engineering applications including multi-objective optimal control design and structural-acoustic design for minimum sound transmission. We then discuss some algorithmic development of the cell mapping methods for various applications. Discussions will then be directed to the future directions of the cell mapping based research in the framework of evolutionary computing and optimization.



Short Biography

Dr. Jian-Qiao Sun earned a BS degree in Solid Mechanics from Huazhong University of Science and Technology in Wuhan, China in 1982, and a PhD in Mechanical Engineering from University of California at Berkeley in 1988. He worked for Lord Corporation at their Corporate R&D Center in Cary, North Carolina. Dr. Sun jointed the faculty in the department of Mechanical Engineering at the University of Delaware as an Assistant Professor in 1994, was promoted to Associate Professor in 1998 and to Professor in 2003. He joined University of California at Merced in 2007, and is currently a professor and chair of the Department of Mechanical Engineering in School of Engineering. He is currently the Editor-in-Chief of International Journal of Dynamics and Control published by Springer.

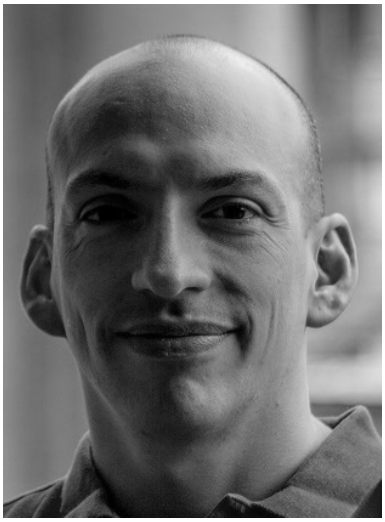
Manuel Bogoya

A generalization of the averaged Hausdorff distance Δ_p

Pontificia Universidad Javeriana, Colombia

Talk Abstract

The averaged Hausdorff distance Δ_p is an inframetric which has been recently used in evolutionary multi-objective optimization (EMO). We introduce a new two-parameter performance indicator $\Delta_{p,q}$ which generalizes Δ_p as well as the standard Hausdorff distance. For $p,q \geq 1$ the indicator $\Delta_{p,q}$ (that we call the (p,q)-averaged distance) turns out to be a proper metric and preserves some of the Δ_p advantages. We show several properties of $\Delta_{p,q}$, including a geometrical role for p and q, and provide a comparison with Δ_p and the standard Hausdorff distance.



Short Biography

Manuel Bogoya received his PhD in operator theory from CINVESTAV research center in Mexico (2010). His research also includes statistical models for education, spectral distribution, and Toeplitz operators. He is currently associate professor at Pontificia Universidad Javeriana, Bogotá-Colombia.

Carlos Hernández

Cell Mapping Methods for Multi-objective Optimization

Mutuo Financiera, Mexico

Talk Abstract

In the last decades there has been an increased interest to solve multi-objective optimization problems. This kind of problems appear in almost every aspect of life, since it is typical to have several objectives that are in conflict. The focus of the area is to find one or several best trade-off solutions (that form the so-called global Pareto set/front). Most state-of-the-art algorithms aim to find an approximation of these sets. However, in most of the cases they do not give further information about the problem. In this talk, we will focus on the design and study of the cell mapping methods. Such methods are capable to exploit information such as basins of attraction, local optimal solutions and neighborhood information. This information is useful to compute different sets of interest for the decision maker besides the global Pareto set/front. These sets include the local Pareto set/front and the set of nearly optimal solutions which can be useful as backup solutions. Further, the set of lightly robust optimal solutions which is in particular important when the problems are subject to uncertainties. We will highlight the usefulness of the cell mapping methods in several real world applications from optimal control. Finally, we will discuss future directions of the cell mapping for problems with uncertainty.

Short Biography

Carlos was born in Tepic Nayarit. He started his academical career in the Instituto Tecnológico de Tepic. Later he studied his masters at CINVESTAV-IPN for which he obtained the award for the best thesis in artificial intelligence by the Mexican Society of Artificial Intelligence. In 2017, he obtained his Ph.D. at CINVESTAV-IPN for which he obtained the Rosenblueth Award. Currently, he is CTO and co-founder at Mutuo Financiera. His primary research topics include set oriented numerics, multi-objective optimization, and optimization under uncertainty.

Carlos Coello Coello

Metaheurísticas Bio-Inspiradas: Resolviendo Problemas como la Naturaleza lo Haría

CINVESTAV-IPN, Mexico

Talk Abstract

En esta plática se hablará sobre las metaheursticas, con un particular énfasis en aquellas que tienen una inspiración biológica (p.ej., los algoritmos evolutivos, los algoritmos cumulares y las colonias de hormigas). Se pondrá particular énfasis en la forma en que este tipo de herramienta computacional ha permitido resolver problemas de gran complejidad en tiempos razonablemente cortos, mediante la simulación de ciertos procesos de la naturaleza tales como la evolución natural. En la parte final de la plática se discutirán brevemente algunas de las áreas más prometedoras de investigación futura en esta área.

Short Biography

Carlos Artemio Coello Coello received a PhD in Computer Science from Tulane University (USA) in 1996. His research has mainly focused on the design of new multi-objective optimization algorithms based on bio-inspired metaheuristics. He currently has over 450 publications which, according to Google Scholar, report over 41,500 citations (with an h- index of 80). He has received several awards, including the National Research Award (in 2007) from the Mexican Academy of Science (in the area of exact sciences), the 2009 Medal to the Scientific Merit from Mexico City's congress, the Ciudad Capital: Heberto Castillo 2011 Award for scientists under the age of 45, in Basic Science, the 2012 Scopus Award (Mexico's edition) for being the most highly cited scientist in engineering in the last 5 years and the 2012 National Medal of Science in Physics, Mathematics and Natural Sciences from Mexico's presidency (this is the most important award that a scientist can receive in Mexico). He is also the recipient of the prestigious 2013 IEEE Kiyo Tomiyasu Award, "for pioneering contributions to single- and multiobjective optimization techniques using bioinspired metaheuristics". Since January 2011, he is an IEEE Fellow. He is currently Full Professor with distinction at the Computer Science Department at CINVESTAV-IPN in Mexico City, Mexico.

III

Special Sessions

Set Oriented Methods

Chair: Dr. Carlos Ignacio Hernández

Set oriented methods have proven to be very efficient in the numerical treatment of various classes of global optimization problems in academy and industry and are widely used in many fields, such as Engineering and Finance. This special session serves as a platform for researchers fromall over the world to present and discuss recent advances in set orientednumerical methods in particular in the context of optimization. Methods of this kind iterate (or evolve) entire sets instead of consideringpoint-wise iterative methods and are thus in particularadvantageous if a thoro ugh investigation of the entire domain is required and/or the solution set is not given by a singleton.

Topics

- Cell mapping techniques.
- Subdivision techniques.
- Continuation methods.
- Swarm-like strategies.
- Methods for all kinds of optimization problems, including: scalar, multi-objective, bi-level, and dynamic optimization problems, applications to real-world problems.

Discrete Optimization

Chair: Dra. Marcela Quiroz Castellanos

Applications of discrete optimization problems arise in engineering, science, economics, and everyday life. It is common to find in many real-world linear, as well as nonlinear programming, that all, or a fraction of variables are restricted to be integer, yielding integer or mixed integer-discrete-continuous problems. Many of these problems are computationally intractable. The approaches that are addressing these problems include: traditional optimization techniques, efficient preprocessing schemes, decomposition techniques, fast heuristics, metaheuristics and hybrid methods. This special session serves as a platform for researchers from all over the world to present and discuss recent advances and perspectives in the mathematical, computational and applied aspects of all areas of integer programming, combinatorial optimization and mixed integer-discrete-continuous optimization.

Topics

- Single and multi-objective optimization.
- Deterministic approaches.
- Approximation algorithms.
- Randomized algorithms.
- Heuristics.
- Meta-heuristics.
- Simulation.
- Stochastic programming.
- Real-world applications.

Digital Analysis and Processing

Chairs:

- **Dr. Javier Flavio Vigueras Gómez**
- **Dr. Jean-Bernard Hayet**
- **Dr. Guadalupe Dorantes Méndez**
- **Dr. Aldo Rodrigo Mejía Rodríguez**

Advances in the fields of digital signal processing (detection, recognition, and processing of digital audio and video, seismology, control systems, biomedical and satellite signals, to name a few) lead to a wide-spread usage of optimization approaches. These tasks often employ optimization schemes as they intend to find the "best" solution for some criteria. Furthermore, the choice of the optimization approach sternly affects the performance of the overall task, concerning efficiency measures like accuracy and runtime, among others. The goal of this special session is to allow researchers to present recent advances, perspectives, and applications in both, theoretical and practical aspects, of optimization approaches contributing to the improvement of analysis and processing of digital signals.

Topics

- Event detection in time series.
- Object recognition.
- Combinatorial approaches.
- Probabilisitic approaches.
- Soft computing approaches.
- Multi-objective optimization in signal processing.
- Complexity analysis of algorithms.
- Image segmentation.
- Applications.

Women at NEO

Aim of the session

Women at NEO is a space to promote and intensify research, discussion, and collaboration among the female NEO community. We take time at NEO also for networking and meeting consolidated and young researchers, as well as involved students. One of the goals of W-NEO is to inspire, engage and advice students who are currently working—or planning to work—on optimization subjects lead by the female professors. This section consists of some talks and a short meeting. We will encourage the setting up of specific woman networks with common interests.

It is worth to notice that male researchers/students are also welcome in every part of this session!

Talks

- Perla Juárez. *Pool-based Genetic Programming with Speciation, Bloat Control and Local Search*
- Claudia Orquidea López. *Packing problem as a mixed integer non-linear model using formulation space search.*
- Marta Cabo. *Beam Search: A Tree Search Heuristic and its Applications to Cutting and Packing Problems.*
- Lourdes Uribe. *An overview of constraint handling methods for MOPs*
- Lourdes Uribe. *The Δ_p Newton Method*
- América Morales. *A review in autonomous driving: present and future trends.*
- Miriam Pescador. *Automatic Design of Multiobjective Optimization Evolutionary Algorithm Based on Decomposition.*
- Laura Cruz Reyes. *DPEM-HH: A population evolvability-based multi-objective hyperheuristic to solve dynamic multi-objective optimization problems.*
- Christian Lizbeth Noguez Moreno. *Efficiency of Mexican universities using minimum distance approach in data envelopment analysis.*
- Claudia Gómez-Santillan. *Obtaining inference rules through compensatory fuzzy logic for decision problems with imperfect knowledge.*

Participants

Name	Institution
Abril Torres Mendez	CINVESTAV-SALTILLO
Adriana Farfán Chavez	ESFM-IPN
Adriana Ivonne Monter	Universidad Autónoma de Hidalgo
Adriana Lara	ESFM-IPN
América Berenice Morales Díaz	CINVESTAV-SALTILLO
Christian Lizbeth Noguez Moreno	UAM-Azcapotzalco
Claudia Gomez-Santillan	Instituto Tecnológico de Ciudad Madero
Claudia Orquídea López Soto	UNAM
Fernanda Beltrán	CINVESTAV-IPN
Iris Yonitzi Martínez González	ESCOM-IPN
Jesica Flores Álvarez	ESCOM-IPN
Karla Rodriguez Guevara	ESFM-IPN
Laura Cruz-Reyes	Instituto Tecnológico de Ciudad Madero
Lourdes Uribe	ESFM-IPN
Marcela Quiroz	Universidad Veracruzana Xalapa
María José Salmerón Contreras	ESCOM-IPN
Marta Cabo	ITAM
Mercedes Pérez-Villafuerte	Instituto Tecnológico de Tijuana
Michelle Caballero Ramírez	ESCOM-IPN
Miriam Pescador-Rojas	CINVESTAV-IPN
Nadia Gabriela Escobedo Domínguez	ESCOM-IPN
Perla Juárez	Instituto Tecnológico de Tijuana
Sabrina Erika Pensamiento Robledo	ESCOM-IPN
Sofía Alejandra Mora Arroyo	ESCOM-IPN
Stefany Paola Corona Soto	ESFM-IPN
Yazmín Maldonado	Instituto Tecnológico de Tijuana

IV Contributed Talks

List of Talks

September 26

- Oliver Schütze.*On Continuation Methods for Continuous MOPs*
- L. A. Quezada-Téllez , Saúl Zapotecas-Martínez and Abel García-Nájera. *Multiobjective Optimization of an Investment Portfolio: A Preliminary Study of the American, European, and Mexican Stock Markets*
- Alberto Rodríguez Sánchez, Antonin Ponsich, Antonio López Jaimes and Saúl Zapotecas-Martínez.*Using a parallel Tabu search to approximate Uniform design*
- Esteban Gamboa García, Saúl Zapotecas-Martínez and Karen Miranda. *On the Deployment of Radio Frequency Identification Readers: A Multiobjective Perspective*
- J.N Martínez-Castelán and M.G. Villarreal-Cervantes .*Concurrent Design of a Passive Bipedal Walker using Differential Evolution Algorithm*
- J.S. Pantoja-García, M.G. Villarreal-Cervantes and C.V García-Mendoza. *Concurrent design of a bipedal lower-limb by using differential evolution*
- Roides Javier Cruz Lara and Efrén Mezura Montes. *Engineering Optimization by Combining an Adapted Nelder-Mead Method with Differential Evolution*
- León Dozal.*Analysis of similarity measures of protein sequences applied to trees in genetic programming*
- Leonardo Trujillo, Perla Juárez, Mario García-Valdez, Francisco Fernández de Vega and Francisco Chavez. *Pool-based Genetic Programming with Speciation, Bloat Control and Local Search*
- Cristian Sandoval, Leonardo Trujillo, Luis C. González and Oliver Schütze.*Yet Another Guiding Scheme for Multi Objective Evolutionary Algorithms as produced by Genetic Programming*
- Claudia Orquidea López and J.E. Beasley.*Packing problem as a mixed integer nonlinear model using formulation space search*
- Marta Cabo. *Beam Search: A Tree Search Heuristic and its Applications to Cutting and Packing Problems.*
- Isaac López López, Carlos Segura González and Guillermo Sosa Gómez.*Metaheuristics in the Optimization of Cryptographic Boolean Functions*
- Juan Ceballos Corral and Alejandro Alvarado Iniesta.*Multi-Objective Integer Linear Optimization of a Distribution Problem of Brand-New Tractor Units*
- Sergio Luis Pérez Pérez, Carlos E. Valencia, Carlos A. Alfaro, Marcos César Vargas Magaña and Francisco Javier Zaragoza Martínez.*Analysis of Dimensionwise Variation Heuristics for the Multidimensional Assignment Problem*
- Jesus Fernández and Carlos Hernández.*Many-objective Portfolio Optimization for Natural Gas Loans*

September 27

- Oliver Shütze, Adriana Lara, Lourdes Uribe and Fernanda Beltrán. *On the Design of Hybrid Evolutionary Multi-objective Optimization Algorithms for Constrained MOPs*
- Lourdes Uribe, Adriana Lara and Oliver Schütze.*An overview of constraint handling methods for MOPs*
- Darian Reyes Fernández de Bulnes and Yazmín Maldonado.*VHDL by MOEA: a tool for Multi-objective Optimization in High-Level Synthesis*
- Oliver Cuate and Oliver Schütze.*Using the Pareto Explorer Framework for the Decision-making Processes in Real-world Applications*
- Oliver Cuate and Oliver Schütze. *Variation Rate: an Alternative to Maintain Diversity in Decision Space for Multi-objective Evolutionary Algorithms*
- Teodoro Macias-Escobar, Laura Cruz-Reyes, Bernabé Dorronsoro, Héctor Fraire-Huacuja, Claudia Gómez-Santillan, Nelson Rangel-Valdez and Daniel Martínez-Vega.*DPEM-HH: A population evolvability-based multi-objective hyperheuristic to solve dynamic multi-objective optimization problems*
- David Laredo, Zhaoyin Chen, Oliver Schütze and Jian-Qiao Sun . *A Neural Network-Evolutionary Computation Framework for Remaining Useful Life Estimation*
- Luis Muñoz, Leonardo Trujillo and Sara Silva.*Transfer Learning of Evolved Feature Transformations*
- Heriberto Cruz Hernández and Luis Gerardo de la Fraga. *A method to optimize the Order Type Maximal Perturbation through multiple single point displacements*
- Saúl Martínez Díaz, Maarouf Saad and Jawhar Ghommam.*Depth estimation for a monocular vision system*
- V. A. Adeyemi, A. Bonilla-Rodriguez, R. Y. Serrato Andrade, G. Entrambasaguas-Leon, Y. Sandoval-Ibarra, E. Tlelo-Cuautle and J. C. Núñez-Perez. *Dynamical and Numerical Analysis of Chen Chaotic Oscillator*
- Jesús Antonio Álvarez-Cedillo, Teodoro Álvarez-Sánchez and Jacobo Sandoval Gutierrez.*Implementation Of An Object Recognition System Based On Deep Learning In A Rpas*
- Jesús Antonio Álvarez-Cedillo, Teodoro Álvarez-Sánchez and Jacobo Sandoval Gutierrez.*Real-Time Weapon Recognition Using Deep Learning*
- Alejandro Martin Gomez and Javier Flavio Vigueras Gómez.*Probabilistic Uniformity as a Similarity Measure Robust to Lighting Changes*
- Víctor R. López-López, Leonardo Trujillo and Pierrick Legrand. *Improving a vision-based SLAM system using Novelty Search*
- América Morales.*A review in autonomous driving: present and future trends*

September 28

- Mercedes Perez-Villafuerte, Laura Cruz-Reyes, Nelson Rangel-Valdez, Claudia Gomez-Santillan, Héctor Fraire-Huacuja, Ma. Lucila Morales-Rodriguez and Alejandro Estrada-Padilla.*A study of the effect of the decision maker profile in the decision-making process*
- Gabriela Salas-Tovar, Claudia G. Gomez-Santillan, Laura Cruz-Reyes, Héctor Fraire-Huacuja, Alejandro Estrada-Padilla, Nelson Rangel-Valdez.*Obtaining inference rules through compensatory fuzzy logic for decision problems with imperfect knowledge*
- Ángel David Téllez Macías, Antonin Ponsich, Roman Anselmo Mora Gutierrez and Eric Alfredo Rincon Garcia*Multi-objective optimization of the supply chain design and operation*
- Christian Lizbeth Noguez Moreno, Roman Anselmo Mora Gutierrez, Eric Alfredo Rincón Garcia and Antonin Ponsich.*Efficiency of Mexican universities using minimum distance approach in data envelopment analysis*
- Miriam Pescador Rojas.*Automatic Design of Multiobjective Optimization Evolutionary Algorithm Based on Decomposition*
- Javier Gurrola-Ramos, Arturo Hernández-Aguirre and Oscar Dalmau-Cedeño.*COLSHADE-Levy for Constrained Optimization*
- Lourdes Uribe, Adriana Lara, Günter Rudolph and Oliver Schütze.*The Δ_p Newton Method*
- Luis A. Quezada-Téllez, Saúl Zapotecas-Martínez, Oliver Schütze and G. Fernández-Anaya.*On the Stability in Dynamic Systems to Analyze Evolutionary Multiobjective Algorithms*

On Continuation Methods for Continuous MOPs

Oliver Schütze

Computer Science Department
Cinvestav-IPN
Mexico City, Mexico
schuetze@cs.cinvestav.mx

In many applications the problem arises that several objectives have to be optimized concurrently leading to multi-objective optimization problems (MOPs). As a general example, two common goals in product design are certainly to maximize the quality of the product and to minimize its cost. Since these two goals are typically contradicting, it comes as no surprise that the solution set – the so-called Pareto set – of a MOP does in general not consist of one single solution but rather of an entire set of solutions. More precisely, the Pareto set of a continuous MOP typically forms at least locally a (k-1)-dimensional manifold, where k is the number of objectives involved in the problem. In this talk, we propose the Pareto Tracer (PT), a continuation method that makes use of the geometric property of the Pareto set. The particularity of the PT is that it separates the decision and the weight space in the computations whenever possible leading to significant reduction in the overall computational cost. We demonstrate the benefit of the novel solver on several benchmark problems and finally give paths for future work to extend the applicability of the method.

Multiobjective Optimization of an Investment Portfolio: A Preliminary Study of the American, European, and Mexican Stock Markets

Luis A. Quezada-Téllez[a], Saúl Zapotecas-Martínez[a], Abel García-Nájera[a], Oliver Schuetze[b]

[a]Departamento de Matemáticas Aplicadas y Sistemas
Universidad Autónoma Metropolitana Cuajimalpa
Av. Vasco de Quiroga 4871, Col. Santa Fe Cuajimalpa, Ciudad de México. C.P. 05348
email: {lquezada,szapotecas,agarcian}@correo.cua.uam.mx

[b]Departamento de Computación
CINVESTAV-IPN
Av. IPN No. 2508, Col. San Pedro Zacatenco, Ciudad de México. C.P. 07360
email: schuetze@cs.cinvestav.mx

This work analyses the multiobjective optimization of an investment portfolio. The traditional model of Markowitz considers the expected returns of financial assets to make the best selection of the portfolio. There are two main criteria to regard: expected return and risk. In such case, the Markowitz model uses a mean-variance analysis to determinate the efficient frontier of an investor. In this work, we study the investment portfolio introducing an additional criterion, namely the variation coefficient. Several instances of portfolios are investigated through real data from the American, European, and Mexican stock markets. In our study, we analyze the performance of traditional multiobjective evolutionary algorithms (MOEAs) based on three principles: Pareto dominance, hypervolume indicator, and decomposition. According to our results, we noticed that a hypervolume-based MOEA can approximate, in a better way, the Pareto frontier of these instances.

Using a parallel tabu search to approximate uniform design

Alberto Rodríguez Sánchez[a], **Antonin Ponsich**[a],
Roman A. Mora Gutiérrez[a], **Eric A. Rincón García**[c],
Antonio López Jaimes[b], **Saúl Zapotecas Martínez**[b]

[a]Dpto. de Sistemas, Universidad Autónoma Metropolitana Azcapotzalco
[b]Dpto. de Matemáticas Aplicadas y Sistemas, Universidad Autónoma Metropolitana Cuajimalpa
[c]Dpto. de Ing. Eléctrica, Universidad Autónoma Metropolitana Iztapalapa
Ciudad de México, Mexico
`{al2161801914,aspo,mgra,rigaeral}@azc.uam.mx, alopez@correo.cua.uam.mx, saul.zapotecas@gmail.com`

In Multi-objective Optimization (MO), diversity assessment is one of the most important concern in order to produce an approximated set of solutions evenly distributed over the Pareto front. To deal with this issue, recent algorithms such as MOEA/D[2] make use of a uniformly scattered set of reference points/vectors that indicates search directions in the objective space. This issue becomes critical in Many-objective Optimization, promoting the development of many generation techniques having a rich underlying theory mainly arising from chemistry and statistics areas.
Among these methods, the Uniform Design (UD) is based on the minimization of a discrepancy metric, which measures how well equidistributed the points are in a sample space. Of particular interest in this work is the centered L_2 discrepancy metric proposed in [1]. An exponentially increasing number of candidate sets can be generated using the Good Lattice Point (GLP) technique, which involves a huge computational cost (memory and time). It was demonstrated that the problem of finding a uniform design under a given discrepancy metric is NP-hard when the number of runs, $n \to \infty$ and the number of factors, $s > 1$.
In order to solve this optimization problem, a parallel Tabu Search (TS) is implemented in this work. A specific feature is the tabu list that only reports "generator parameters", which are the input needed by the GLP algorithm to generate the set of final reference points. The implementation of the TS proposed here can handle 792 runs, 8 factors and 240 levels, which is significantly higher than those reported in the official tables (see `http://www.math.hkbu.edu.hk/UniformDesign/`).
The best reference sets founded by TS were subsequently used to solve two classical MO problems with MOEA/D (using the Tchebycheff scalarizing function). The results are compared with those of the Simplex Lattice Design (SLD) in terms of the Hypervolume (HV) and Δ-diversity indicators. Table 1 reports median and standard deviation values. Results highlight that the UD allows a significant improvement, particularly regarding diversity and when the number of objectives increases.

	DTLZ2						DTLZ7					
	HV			Δ			HV			Δ		
# Obj.	3	5	8	3	5	8	3	5	8	3	5	8
SLD	**1.0602 (0.0007)**	**1.8405 (0.0001)**	**3.0779 (0.2421)**	0.6834 (0.0041)	1.8358 (0.0024)	1.6912 (0.0899)	**993.0 (42.9)**	**108067.0 (10049.3)**	78564642.4 (17331854.3)	1.30312 (0.00653)	1.52916 (0.01645)	1.50361 (0.04593)
UD	1.0598 (0.0009)	1.7824 (0.0017)	2.2103 (0.6553)	**0.4286 (0.0032)**	**0.5968 (0.0026)**	**0.4361 (0.0023)**	990.0 (27.7)	105269.9 (82.0)	**81425512.7 (3697398.6)**	**1.16453 (0.01207)**	**1.00264 (0.00731)**	**0.92790 (0.00337)**

Table 1: Comparison between MOEA/D with Uniform and Simplex Lattice Design

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Concurrent Design of a Passive Bipedal Walker using Differential Evolution Algorithm

Martínez-Castelán J.N.[a], Villarreal-Cervantes M.G.[a]

[a]Instituto Politécnico Nacional - CIDETEC
Laboratorio de Diseño Mecatrónico Óptimo
Av. Juan de Dios Bátiz s/n esq. Miguel Othón de Mendizábal, Col. Nueva Industrial Vallejo,
Del. Gustavo A. Madero, Ciudad de México, C.P. 07700.
e-mail: n.mtz.cas@gmail.com, mvillarrealc@ipn.mx

Abstract

Commonly, the design of Passive Bipedal Walkers (PBWs) implies determining a set of physical parameters that generates a limit cycle in its sagittal plane only. Nevertheless, the design of a PBW with a more realistic behavior, must also consider its frontal plane dynamics. Since frontal and sagittal dynamic models are nonlinear and discontinuous, the search of optimal structural parameters cannot be carried out efficiently through gradient based optimization methods. Therefore, it is proposed to implement a stochastic technique in order to solve a concurrent design problem that allows a simultaneously achievement of operating requirements of both system planes. Thus, a concurrent approach is stated as a nonlinear discontinuous dynamic optimization problem, where its solutions search is addressed through the use of Differential Evolution (DE) algorithm. Simulation results demonstrate that frontal and sagittal dynamic behaviors of the best design get coupled by a common gait period T, which means that PBW is capable of walking.

Concurrent design of a bipedal lower-limb by using differential evolution

Pantoja-García J.S. [a], Villarreal-Cervantes M.G.[a], García-Mendoza C.V.[b]

Instituto Politécnico Nacional - CIDETEC [a], ESCOM [b]
e-mail: jpantojag@alumno.ipn.mx, mvillarrealc@ipn.mx, cgarciam@ipn.mx

Abstract

The present research aimed to enhance the relationship between conflicting objectives in the concurrent bipedal lower-limb design. Hence, a multi-objective optimization problem is formulated to promote the reconfigurability designs with different tradeoffs. Three different differential evolution variants are employed to solve the optimization problem. Statistical results showed that the region based selection approach and external archive into the differential evolution algorithm promotes the convergence, diversity, and capacity of the Pareto front. Furthermore, the obtained bipedal lower-limb can suitably perform the gait path.

Engineering Optimization by Combining an Adapted Nelder-Mead Method with Differential Evolution

Roides Javier Cruz Lara[a], Efrén Mezura Montes[b]

National Laboratory of Advanced Informatics (LANIA) A.C.
Rébsamen 80, Centro, Xalapa, Veracruz, 91000, MEXICO
rcruz_mca16@lania.edu.mx

[b] Artificial Intelligence Research Center
University of Veracruz
Sebastián Camacho 5, Centro, Xalapa, Veracruz, 91000, MEXICO
emezura@uv.mx

In this paper, a Hybrid Algorithm based on the Nelder Mead Method and the Differential Evolution (HNMDE) is presented. The design of the algorithm is based on a new approach of hybridization that aims to increase the synergy between the local and global search engines, as well as guarantee a greater balance between the exploration and exploitation operations in the minimization of global optimization problems. The fundamental guideline of the approach states the distribution of several instances of a local search engine in random points of the search space to guarantee the exploration. However, operators of local search methods only exploit a relatively small neighborhood around the starting point. Therefore, it is proposed that a global search engine must be responsible for indicating to the different local search instances, where the most promising regions are located. In addition, the work must be balanced: this means that the function evaluations budget destined for each search engine must not be disproportionate. The selected local search engine was the Nelder Mead method. This is a derivate-free method, proposed in [1] for the minimization of an N dimensional function by performing reflection, expansion or contraction operations on a simplex in the search space. The simplex is adapted to the "local landscape", lengthening by long inclined planes, changing direction when finding a descent at a certain angle and contracting around the neighborhood of a minimum. The original procedure of the Nelder Mead Method was modified for hybridization purposes. An operator based on the current-to-best differential mutation was added: $x_{new} = x_{r_1} + F(best - x_{r_1}) + (1 - F)(x_{r_2} - x_{r_3})$. Note, that in the third member of the operator the scale factor is $1 - F$ which is the complement of $F = (0.3, 0.9)$. This modification follows the proposed approach and seeks to maintain a balance between the elitist exploitation and the random exploration members of the operators. This operator is applied when none of the original operators of the NMM are able to enhance the value of the objective function for the worst point in the simplex. The selected global search engine was the Differential Evolution (DE). This is an efficient evolutionary algorithm for the global optimization in continuous spaces proposed by Storn and Price. The DE as a parallel direct search method that uses a set of NP vectors of N dimensions $x_{i,G}$ with $i = \{1; 2; ...NP\}$ as population for each generation G. One of the most significant components of the DE is its the mutation operator defined by the equation: $v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G})$. The mutated vector $v_{i,G+1}$ is generated from three randomly selected vectors, such that the random indices satisfy the inequality: $i \neq r_1 \neq r_2 \neq r_3$. Then $v_{i,G+1}$ is calculated by adding to the first vector the weighted difference between the other two vectors. Where $F > 0$ is a real constant which determines how wide the difference will be [2]. The DE was modified using a new operator based on the current-to-best operator: $v_{m,G+1} = x_{m,G} + F(x^r_{l,G} - x_{r_1,G}) + (1 - F)(x_{r_2,G} - x_{r_3,G})$. Where $m = \{1, 2, .., NS\}$ indicates the position in simplex S_k where the DE will operate and NS is the number of simpleces. The individual x^r_l is randomly selected from X_l, the best individuals of each simplex.
The general procedure of HNMDE uses a population X composed by NS simplces or sub-populations of size $N+1$. The initial simpleces are generated using an initialization strategy that locates the edges of the simpleces around the inner neighborhood of the search space bounds. In the generation G, each instance

$k = \{1, 2, ..., NS\}$ of the Modified Nelder Mead method (MNM) will perform a local search on the simplex S_k. Then, the DE is applied to an elite individual $x_{m,G}$ of each simplex. This individual will change in each generation according to the m index, which increases by one per generation and takes values from 1 to NS. When m reaches the value of NS it is reset to 1. For constraint handling both search engines use the simple feasibility rules proposed by Deb in [3]. Also, a boundary rule for the design variables is applied before any function evaluation. The algorithm was obtained through the experimental design which included the analysis of each component separately and then combined.
Six problems of Mechatronic Design Optimization were solved. The first three problems: MCS1, MCS2, and MCS3 are cases study of the "Optimal Synthesis of a Four-Bar Mechanism", which consists of minimizing the mechanism trajectory error respect to the desired trajectory [4] [5]. The number of variables is equal to 15, 6 and 19 for MCS1, MCS2, and MCS3 respectively. Similarly, in the two cases study of the "Optimal Synthesis of a Final Fingertip Effector" (GCS1 and GCS2), it is necessary to maximize the accuracy of the gripper fingers by minimizing the error of the trajectory of the coupler. In both study cases, the number of design variables is 15 [6]. The kinematic analysis of mechanisms conceives a noncontinuous non-linear function that includes trigonometric and power operations over the design variables. The search space is restricted by linear functions. The last problem solved is the "Optimization of the Energy Generation in an Isolated Smart Grid" (SCS1). For this problem, it is considered every hour of the day as an optimization problem where the limits for the design variables can vary according to what happened in the previous hour [7] [8] [9]. The objective function is a quadratic function of four variables, constrained by two linear inequalities and one linear equality. The descriptive and inferential statistical tests showed a competitive performance of HNMED versus the ED/rand/1/bin and C-LSHADE a variant of LSHADE to solve constrained optimization problems proposed in [10]. However, the number of evaluations of the objective function used was significantly lower for all optimization problems. New solutions where found for GCS1, MCS2, SCS1. In the case of MCS2, SCS1 a better function value was reached.

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Analysis of Similarity Measures of Protein Sequences Applied to Trees in Genetic Programming

León Dozal[a]

[a]Centro de Investigación en Ciencias de Información Geoespacial, A.C.
Circuito Tecnopolo Norte No. 117, Fracc. Tecnopolo II, Pocitos, Aguascalientes, CP 20313, México
ldozal@centrogeo.edu.mx

Two methods for similarity measure between two binary trees are proposed and analyzed. The first step for both methods is to represent each tree as a sequence of functions and terminals. This is done by a preorder-inorder traversal of the tree, which is sufficient to represent the tree uniquely. The second step describes how the sequences, unique representations of the trees, will be compared. One similarity measure is computed by applying the well known Needleman-Wunsch method, for finding similarities in the amino acid sequences of two proteins, as was originally proposed. The other one consists in applying it together with a replaceability matrix. The original Needleman-Wunsch computer method compares all possible pair combinations of amino acids sequences by representing them in a two-dimensional array. The similarity between sequences is defined as the largest number that results from the sum of all matches that can be obtained, less any penalty factor produced by allowing all possible insertions or deletions. As their authors stated, the sophistication of the sequence comparison is increased if each match and mismatch value is made a function of any theory concerned with the significance of a pair of amino acids, like a replaceability matrix also known as Point Accepted Mutation (PAM) matrix. The PAM matrix is constructed by calculating the probability of replacement of each function/terminal by another, as well as the probability of functions/terminals to remain unchanged in two consecutive generations. These methods, search for structural and functional similarities in trees and could be used to determine a distance among them for promoting population diversity in genetic programming (GP).

The comparison of sequences can be deceptive because of the different lengths and composition of the sequences, but the most problematic issue is the occurrence of deletions/insertions in the sequences being compared, because they increase the matching of unrelated sequences. For this reason, it becomes mandatory to evaluate the significance of sequences relationship obtained by the proposed similarity measures.

In this way, the experiments are devoted to evaluate and compare the statistical significance of both similarity measures applied to four common standard problems in GP research, that are: artificial ant, quartic and rastrigin regression, and even-5-parity.

A method for obtaining an estimate of statistical significance is to compare a query sequence with randomly permuted versions of a potentially related sequence. Each of the generated permutations retains identical length and functions and terminals composition of the original sequence, moreover, all are valid preorder-inorder traversals of a tree. The similarity scores of all the comparisons are determined and averaged, and standard deviation is computed. Then, each similarity score is compared with the mean, similarities that are 3.0 or more standard deviations above the mean can reasonably be expected to represent authentic relationships.

Results showed that Needleman-Wunsch and PAM similarity methods are statistical significant. But results also showed that the similarity measure that use the PAM matrix demonstrate to be more sensitive and selective method. For this reason, this is a better option to use in promoting diversity in GPs.

Pool-based Genetic Programming with Speciation, Bloat Control and Local Search

Leonardo Trujillo[a], **Perla Juárez-Smith**[b], **Mario García-Valdez**[c], **Francisco Fernández de Vega**[d], **Francisco Chavez**[e]

[a,b,c]Instituto Tecnológico de Tijuana

Tijuana, BC, México

{leonardo.trujillo, pjuarez, mario} @tectijuana.edu.mx

[d,e]Universidad de Extremadura

fcofdez@unex.es, frchavez@gmail.com

This work centers around a unique genetic programming (GP) approach, that integrates several design choices that aim at solving some of the lagging issues in standard GP systems. The method combines a numerical local search method and a bloat-control mechanism. The former provides a directed search operator to work in conjunction with standard syntax operators that perform more exploration in design space. Moreover, by combining both, the system is able to produce highly parsimonious solutions, and reduce the cost of performing the local optimizations of solution candidates. For bloat control the neat-GP algorithm is used, a strategy that relies on speciation and fitness sharing to control code growth [1]. The LS approach is based on [2, 3], where GP trees are augmented with weights for each node which are then optimized with numerical techniques. A Pool-based approach is used to distribute the evolutionary process, in particular, the EvoSpace model can easily exploit the speciation process performed by neat-GP, maintaining the same level of performance as the sequential version even though evolution is now performed in an asynchronous manner. The proposals are extensively evaluated using real-world problems from diverse domains, and the behavior of the search is analyzed with a richier descriptive analysis of the search dynamics and obtained results at several different levels.

Results will show that the proposal compares favorably with a standard approach, and that the pool-based algorithm can be used as a viable alternative for the implementation of a distributed GP system.

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Yet Another Guiding Scheme for Multi-Objective Evolutionary Algorithms as produced by Genetic Programming

Cristian Sandoval[1], Leonardo Trujillo[2], Luis C. González[1] and Oliver Schütze[3]
sr_cristian@outlook.es,leonardo.trujillo@tectijuana.edu.mx,
lcgonzalez@uach.mx,schuetze@cs.cinvestav.mx

[1]Universidad Autónoma de Chihuahua, Facultad de Ingeniería.
[2] Instituto Tecnológico de Tijuana.
[3]Centro de Investigación y de Estudios Avanzados del Instituto Politécnico Nacional (Cinvestav).

The Hypervolume has been acknowledged as a good metric of the quality of a set of solutions in the context of multi-objective optimization problems. Moreover, it has been found that it can also be used to successfully guide the search within MOEA's strategies, e.g. SMS-MOEA. In part, this popularity has been based on its simplicity to be understood and consequently implemented. Unfortunately, the process of calculating the Hypervolume becomes costly with an increase in the number of objectives (dimensions) that are to be considered for a given problem. Based on the hypothesis that surrogate models could be created with the same spirit as the Hypervolume, in this work we propose to generate novel guiding schemes that could replace the Hypervolume as a quality metric or algorithmic guiding aid. We support this hypothesis by using Genetic Programming to evolve mathematical expressions, then evaluating how close they become to the Hypervolume indicator for different set of solutions and Pareto Fronts. To show the robustness of our method, we exhaustively train and test in different datasets and combinations of them, all coming from well-known multi-objective problems proposed by Zitzler et al. In a further experiment, we replaced the Hypervolume-based guiding aid used by SMS-MOEA with the one we evolved with GP, then we contrast it against the original version of the algorithm. Encouraging results show that our proposed solutions are very proximate to the Hypervolume metric as calculated by a Monte Carlo sampling strategy, and better yet with shorter computation time.

Packing problem as a mixed integer non-linear model using formulation space search

C.O. López*[1] and J.E. Beasley†[2]

[1]Faculty of Sciences, National Autonomous University of Mexico, Mexico City, Mexico
[2]Mathematical Sciences, Brunel University, Uxbridge UB8 3PH, UK and JB Consultants, Morden, UK

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Abstract

In this work we present the packing problem as a mixed integer non-linear programming problem which is solved using a heuristic called formulation space search.

The packing problems that we solved consider a circular container, as for the objects to be pack we have two different shapes: circles and squares/rectangles. Each case is considered in an independent manner. The mathematical model that describes the packing problem may take two different objectives, maximize the objects to be packed or maximize the total area covered by the objects to be packed. In both cases, the size of the objects is fixed. Here we introduce an element of choice; the object may or may not be packed. Hence, it is possible that not all the objects considered to be pack will be in the final arrangement. We show how we managed to eliminate a maximization term that arise in one of the constraints of our formulation when working with the rectangle/square case. Computational results are presented for the test instances considered.

*claudia.lopez@ciencias.unam.mx
†john.beasley@brunel.ac.uk; john.beasley@jbconsultants.biz

Beam Search: A Tree Search Heuristic and its Applications to Cutting and Packing Problems

Marta Cabo 1[a]

[a]ITAM
Instituto Autónomo de México
Rio Hondo, 1; Colonia Progreso Tizapán, Del Álvaro Obregón, CDMX.
marta.cabo@itam.mx

Beam Search is a heuristic that uses a tree search structure of nodes and branches analogous to branch and bound, but only a subset of nodes is evaluated in the search tree. At any level, only the nodes considered to be promising are kept for further branching and the remaining nodes are pruned permanently. Its structure lends itself to modeling problems where the solution of the problem may be constructed sequentially.
Following this structure, it is reasonable to think that the first applications of Beam Search where in scheduling problems, as in [?]. The algorithm alternates between searching the tree breadth first and then depth first, with aggressive pruning of the branches at each stage according to a local and global evaluation function, respectively. There is no backtracking and the number of branches at each level of the tree is user defined. Hence, the user somewhat controls the running time of the algorithm and it is polynomial in the size of the problem. Beam search searches the tree from each parent node, creating multiple children. A filtering method discards some children from each parent to reduce the computational burden while ensuring that only promising children are kept for evaluation. The number of children kept at this stage is called the *filter width* (α), and nodes are selected by a local evaluation function that only takes into account the performance of the partial solution represented by that node, without considering its impact on the final solution. For each of the filtered nodes, a global evaluation is performed by constructing a final solution of the problem, with initial conditions set by the filtered nodes. All of the complete solutions are compared, and only β nodes with the best value for the global evaluation function are kept for further investigation. These nodes are called *beam nodes*, and the value β is known as the beam width. Once the global evaluation function is performed, and the β nodes are selected, the search returns to the partial solutions at the local evaluation level and the β nodes become the new parents. Note that when performing the local evaluation, child nodes will only compete with other children branching from the same parent node. However, for global evaluation all children are compared with each other.
Cutting and Packing problems arise in the literature [?] as those where the objective is to pack a set of small items into a big object. Depending on the problem and its application, one may want to minimize the number of big objects needed to pack all small items, or select a subset of small items that gives the maximum profit when packed into a big object.
In this talk, we present in detail the Beam Search algorithm and how it is been applied to different packing problems, with different objectives functions, and decisions. We will explore the good performance of this heuristic in an problem that it did not seem that suited due the solution representation of the search space and the particular characteristics of the heuristic.

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Metaheuristics in the Optimization of Cryptographic Boolean Functions

Isaac López López[a], Carlos Segura González[b], Guillermo Sosa Gómez[c]

Computer Science Department
Center for Research in Mathematics (CIMAT)
Jalisco S/N, Col. Valenciana CP: 36023 Guanajuato, Gto, México
[a]isaac.lopez@cimat.mx [b]carlos.segura@cimat.mx [c]guillermo.sosa@cimat.mx

Introduction

The problem of finding or constructing Boolean Functions (BFs) with high nonlinearity has been significantly researched by the cryptographic community. Cryptographic Boolean Functions (CBFs) were important in information security since the beginning of the computer age. The use of CBFs has diminished nowadays. However, they are still important as a challenge for the cryptographic and metaheuristic communities. The search space is immensely large, let $\mathcal{B}_n$ denote the set of n-variable BFs, the number of BFs in this set is $|\mathcal{B}_n| = 2^{2^n}$, so with more than five variables it is not possible to do an exhaustive search ($|\mathcal{B}_6| = 2^{2^6} \approx 10^{19}$). There is much research on the application of Evolutionary Algorithms (EAs) to the design of CBFs with high nonlinearity. However, their results are not so good as the ones obtained with algebraic techniques.
We hypothesize that the poor performance of currently designed metaheuristics are related to two issues: the definition of the fitness function which might present too many pleteaus and the appearance of premature convergence. As a result, in this work, we propose a new fitness function and a novel Memetic Algorithm (MA) that applies a slightly modified version of Hill Climbing (HC), basic genetic operators and an extension of the Replacement with Multiobjective based Dynamic Diversity Control strategy (RMDDC) [1]. RMDDC is extended by applying a clustering technique. One of the keys of our proposal is to change the replacement strategy with the aim of improving the control of diversity. Particularly, the aim is to delay the convergence of the population by taking account the stopping criterion set by the user. Another of the keys of our proposal is the definition of a new fitness function. Currently, most of the EAs use the nonlinearity as a fitness function [2][3] but this fitness function present huge plateaus. Experimental validation shows that our proposal could attain BFs with higher non-linearity than other methods.

Description of the Method and Results

In this work, we introduce a memetic algorithm for finding CBFs with high nonlinearity. Let $\mathbb{F}_2^n$ denote the set of all binary vectors of length n, $\mathbb{F}_2^n = \{\mathbf{x} : \mathbf{x} = (x_1, ..., x_n), x_i \in \{0,1\}, i = 1, ..., n\}$. The *Walsh Hadamard Transform* (WHT) measures the correlation between a n-variable BF $f(\mathbf{x})$ and the linear function $L_{\mathbf{w}}(\mathbf{x}) = w_1x_1 \bigoplus \cdots \bigoplus w_nx_n$ and is represented as W_f.

$$W_f(\mathbf{w}) = \sum_{\mathbf{x}\in\mathbb{F}_2^n} \hat{f}(\mathbf{x})\hat{L}_{\mathbf{w}}(\mathbf{x}); \qquad \mathbf{w} \in \mathbb{F}_2^n, \tag{1}$$

where $\hat{f}(\mathbf{x})$ is the *polarity truth table* of $f(\mathbf{x})$ and, $\hat{L}_{\mathbf{w}}(\mathbf{x})$ is the *polarity truth table* of $L_{\mathbf{w}}(\mathbf{x})$. The nonlinearity ($N_f$) of $f(\mathbf{x})$ (candidate solution) is calculated using the maximum absolute value of the WHT and represents the minimum Hamming distance between $f(\mathbf{x})$ and the affine functions set $N_f = \min\{d_H(f(\mathbf{x}), A_{\mathbf{w}}(\mathbf{x})) : A_{\mathbf{w}}(\mathbf{x}) = L_{\mathbf{w}}(\mathbf{x}) \bigoplus c, c \in \{0,1\}\}$.
The objective function applied in a metaheuristic has an important impact on its performance. N_f — which is the most commonly applied fitness function — has the problem that it contains huge plateaus because it returns integer values in a small range, so many BFs are mapped to the same value. With the aim of designing a fitness function with less plateaus, we define a new one that gives each BF a value in the reals and it is the C_1 fitness function:

$$N_f = \frac{1}{2}\left(2^n - \max_{\mathbf{w}\in\mathbb{F}_2^n}{}^1|W_f(\mathbf{w})|\right); \quad C_1 = \left(100 \times \eta_1 \times \max_{\mathbf{w}\in\mathbb{F}_2^n}{}^1|W_f(\mathbf{w})|\right)^3 + \eta_2 \times \max_{\mathbf{w}\in\mathbb{F}_2^n}{}^2|W_f(\mathbf{w})|, \tag{2}$$

where $\max^1_{\mathbf{w}\in\mathbb{F}_2^n}|W_f(\mathbf{w})|$ represents the maximum absolute value in the WHT and η_1 is the amount of times that this value appears and $\max^2_{\mathbf{w}\in\mathbb{F}_2^n}|W_f(\mathbf{w})|$ represents the second maximum absolute value in the WHT and η_2 is the amount of times that this value appears. The principle behind the design of the C_1 fitness function is to minimize the occurrence of entries in the WHT that have the maximum absolute value or the second maximum absolute value.
The key of the RMDDC with Clustering (Algorithm 1) is to alter the replacement strategy by applying a clustering technique that takes into account the stopping criterion. The aim of this novel replacement strategy is to attain a dynamic balance between exploration and exploitation. The RMDDC with Clustering (Algorithm 1) operates as follows. First the population of the previous generation and the offspring are combined in the *Current* set (line 3). Then the Current set is evaluated by taking account the WHT maximum value from each individual and its fitness given by C_1. In order to perform an elitist strategy the best individual — the one with minimum fitness — is selected to survive by placing it in the *NewPop* set and

Algorithm 1: RMDDC with Clustering

1 *Input:* Population, Offspring;
2 *Output:* New Population and Clusters;
3 Current = Population ∪ Offspring;
4 **foreach** $I \in$ *Current* **do**
5 $\quad I_{cost}$ = fitness of individual I.
6 Best = Individual with best fitness in Current;
7 NewPop = {Best} ;
`/* The first cluster with one element is formed */`
8 Clusters = {{Best}} ;
9 Current = Current \ {Best} ;
10 $D = D_I - D_I \times T_{elapsed}/T_{final}$;
11 $D_{Cluster} = D_{Cluster_I} - D_{Cluster_I} \times T_{elapsed}/T_{final}$;
12 **while** *|NewPop|<N* **do**
13 $\quad$ **foreach** $I \in$ *Current* **do**
14 $\quad\quad I_{dist}$ = DCN of I in New Pop;
`/* Check which Clusters are not full, the function "Check" returns 0,1 or 2 */`
15 $\quad\quad val$ = Check(Clusters) ;
16 $\quad\quad$ **if** $val = 0$ **then** `/* All clusters are full */`
17 $\quad\quad\quad$ **if** $I_{dist} < D$ **then**
18 $\quad\quad\quad\quad I_{cost}$ = Infinity;
19 $\quad\quad$ **if** $val = 1$ **then** `/* Some clusters are full */`
20 $\quad\quad\quad$ **if** $I_{dist} < D$ & I *could be in a full cluster* **then**
21 $\quad\quad\quad\quad I_{cost}$ = Infinity;
22 $\quad\quad$ **if** $val = 2$ **then** `/* All clusters are not full */`
23 $\quad\quad\quad$ **if** $I_{dist} < D_{Cluster}$ **then**
24 $\quad\quad\quad\quad I_{cost}$ = Infinity;
25 $\quad$ Selected = Individual with best fitness in Current;
26 $\quad$ **if** $Selected_{dist}$ = *Infinity* **then**
27 $\quad\quad$ Selected = Individual with highest I_{dist} in Current;
28 $\quad$ Clusters = Clusters ∪ {Selected};
29 $\quad$ **foreach** $I \in$ *NewPop* **do**
30 $\quad\quad Selected_{dist}$ = Distance of I to Selected;
31 $\quad\quad$ **if** $Selected_{dist} < D$ **then**
32 $\quad\quad\quad$ Clusters[I] = Clusters[I] ∪ Selected;
33 $\quad\quad\quad$ Clusters[Selected] = Clusters[Selected] ∪ I
34 $\quad$ NewPop = NewPop ∪ Selected ;
35 $\quad$ Current = Current \ {Selec};
36 **Return** Population, Clusters

it is removed from the *Current* set (lines 7-9). The D value, which is used to control diversity of the whole population and the $D_{Cluster}$ value, which is used to control diversity in each cluster, are updated (lines 10-11) by taking into account the initial values D_I and $D_{Cluster_I}$, respectively. Until *NewPop* is filled with N individuals (line 12), the following steps are executed (lines 13-35). First, the contribution to diversity of each individual in the *Current* set is calculated (line 14). If the individual does not contribute enough to the diversity, the clustering technique penalizes it by setting its cost to infinity (lines 16-24). Basically, it is penalized when it is too close to a cluster that is already full or when it is closer than $D_{cluster}$. Then the best individual in the *Current* set is *Selected* (S) to survive. In case that all individuals are penalized, the one that contributes most to diversity is chosen (line 27). A new cluster is created by using the new selected individual as the seed (lines 25-28). Then, the clusters are updated with S and the individuals in the *NewPop* set (lines 29-33). Finally S is added to the *NewPop* set and removed from the *Current* set (lines 34-35). Note that D and $D_{cluster}$ are reduced linearly meaning that more exploration is induced in the initial stages, whereas more intensification is performed in the last stages.

Algorithm 2: Memetic Algorithm

Initialization: Generate a initial population P_0 with N individuals. Assign $t = 0$.
Evaluation: Evaluate every individual in the population.
Local Search: Perform a local search for every individual in the population.
Clustering: Each individual makes up a different cluster.
while *not stopping criterion* **do**
$\quad$ **Mating selection:** Perform binary tournament selection on P_t based on the formed clusters in order to fill the mating pool.
$\quad$ **Crossover:** Individuals from the same cluster are crossed with high probability and the child population (CP) created mantain the balancedness.
$\quad$ **Mutation:** Makes exchanges between two distinct truth table entries of each individual in CP.
$\quad$ **Evaluation:** Evaluate every individual in CP.
$\quad$ **Local Search:** Perform a local search for every individual in CP.
$\quad$ **Survivor selection:** Apply the RMDDC with Clustering strategy to create P_{t+1} with **clustering**.
$\quad$ $t = t + 1$

The Memetic Algorithm (Algorithm 2) is similar to the one applied in [1]. Basically, it is a standard memetic algorithm but it applies the clustering technique to perform the replacement. The obtained results are the best known in literature for EAs. Table 1 show the non-linearity obtained for three different values of n, as well as the best-known solutions attained with EAs prior to this research. Both with $n = 10$ and $n = 12$ results could be improved further.

n	MAX	MIN	MED	Best known for EAs [3]
8	116	116	116	116
10	488	488	488	484
12	1988	1988	1988	1976

Table 1: Nonlinearity found for n-variable boolean functions.

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Multi-Objective Integer Linear Optimization of a Distribution Problem of Brand-New Tractor Units

Juan Ceballos Corral
Universidad Autónoma de Baja California

Alejandro Alvarado Iniesta
Universidad Autónoma de Ciudad Juárez

In Mexico, the delivery of brand-new tractor units is mostly performed by road transportation. A set of tractor units, the so-called "*load*", are mounted on a tractor truck which distributes heterogeneous units to different points of delivery. Thus, it is desirable to specify the appropriate load, the appropriate tractor truck, the position of the towed units, and the route of delivery leading to a multi-objective integer linear optimization problem. In this work, we present a case of study performed in a company located in Mexicali, Baja California, Mexico. We use a multi-objective scalarization method namely the augmented weighted Manhattan scalarizing function, which is defined as follows:

$$\min_{x \in \mathbb{Z}^j} \sum_{i=1}^{k} w_i |f_i(x) - z_i| + \alpha \sum_{i=1}^{k} w_i (f_i(x) - z_i) \quad (1)$$
$$\text{s.t.} \quad g(x) \leq 0,$$
$$h(x) = 0.$$

Hereby, z_i denotes the i-th component of the reference point $Z \in \mathbb{R}^k$, $w = (w_1, \dots, w_k)^T$ is the weight vector with $w_i \geq 0,\ i = 1, \dots, k,\ w \neq 0$, and the parameter α, the so-called *augmentation coefficient*, which must be a small positive value. In addition, we perform a search into user defined directions based on a change in the weight space.

Analysis of Dimensionwise Variation Heuristics for the Multidimensional Assignment Problem

Sergio Luis Pérez Pérez[a], **Carlos E. Valencia**[b], **Carlos A. Alfaro**[a]
Marcos César Vargas Magaña[a], **Francisco Javier Zaragoza Martínez**[c]

[a]Banco de México
Legaria 691, Lomas de Sotelo, Ciudad de México, México
sergio10barca@gmail.com, carlos.alfaro@banxico.org.mx, marcos.vargas@banxico.org.mx

[b]Departamento de Matemáticas
Centro de Investigación y de Estudios Avanzados del Instituto Politécnico Nacional
Instituto Politécnico Nacional 2508, San Pedro Zacatenco, Ciudad de México, México
cvalencia@math.cinvestav.edu.mx

[c]Departamento de Sistemas
Universidad Autónoma Metropolitana Azcapotzalco
San Pablo Xalpa 180, Reynosa Tamaulipas, Ciudad de México, México
franz@correo.azc.uam.mx

Abstract

The Multidimensional Assignment Problem (MAP) is a natural extension of the well-known assignment problem. We make an in depth study of dimensionwise variation heuristics and we show the advantages and disadvantages of this techniques when solving instances of MAP of different sizes. The results of computational evaluation show how this technique offers really high quality solutions that are competitive again many other heuristics for MAP.

The Multidimensional Assignment Problem (MAP), abbreviated sAP in the case of s dimensions, is a natural extension of the well-known Assignment Problem (AP). Let $s \geq 2$ be a fixed number of dimensions, a sAP is stated as follows. Let $X_1, X_2, \ldots, X_s$ be a collection of s disjoint sets. Consider all the combinations that belong to the Cartesian product $X = X_1 \times X_2 \times \cdots \times X_s$ such that each vector $x \in X$, has assigned a weight $w(x)$ and $x = (x_1 x_2 \ldots x_s)$ with $x_i \in X_i$ for each $1 \leq i \leq s$. A valid assignment is a collection $A = (x^1, x^2, \ldots, x^n)$ of n vectors if $x^i_k \neq x^j_k$ for each $i \neq j$ and $1 \leq k \leq s$. The weight of an assignment A is given by $w(A) = \sum_{i=1}^{n} w(x_i)$. The objective of sAP is to find an assignment of minimal weight.
The first approach for dimensionwise variation heuristics was proposed by Huang and Lim in 2006 for 3AP. In 2011, Gutin and Karapetyan proposed a new approach to be used for general sAP based on the ideas of Huang and Lim. In 2017, Perez at. al. proposed a generalization of dimensionwise variation heuristics which includes the two approaches previously proposed plus a set of heuristics of this category that were not considered in the first two approaches. The formulation of the Generalized Dimensionwise Variation Heuristics (GDVH) is as follows: for an instance with s dimensions and n vertices on each, select values t such that $2 \leq t < s$. Select $t-1$ proper subsets from $\{1, 2, \ldots, s\}$ such that $F_1 \cap F_2 \cap \cdots \cap F_{t-1} = \emptyset$ and $F_1 \cup F_2 \cup \cdots \cup F_{t-1} \subset \{1, \ldots, s\}$. Next, generate a $n^1 \times n^2 \times \cdots \times n^t$ n-dimensional matrix $C_{i^1, i^2, \ldots, i^t} = w(v^{i^1, i^2, \ldots, i^t})$ as follows:

$$v_d^{i^1, i^2, \ldots, i^{t-1}, i^t} = \begin{cases} r_d^{i^1} \text{ if } d \in F_1 \\ r_d^{i^2} \text{ if } d \in F_2 \\ \ldots \\ r_d^{i^{t-1}} \text{ if } d \in F_{t-1} \\ r_d^{i^t} \text{ otherwise} \end{cases} \quad \text{for } 1 \leq d \leq s \ . \tag{1}$$

A heuristic of this type that chooses a t value is called a DVt heuristic. DV2 heuristics were explored in the previous works of Gutin and Karapetyan in 2011 and DV3 heuristics were explored in the previous work of Perez et. al in 2017. We explore all the DVt heuristics until the case of DV$(s-1)$, which is the biggest version of this set of heuristics that could be considered. We also perform a computational evaluation over instances until 10 dimensions that consider until hundred of millions of variables.
We compare the results obtained against other heuristics that have been developed and show good results on some types of instances of MAP. Some of the considered techniques are the memetic algorithms by Gutin and Karapetyan in 2011, some cross entropy methods by Nguyen et. al. in 2014, the memetic algorithms by Perez et. al. in 2017, among many others.

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Many-objective Portfolio Optimization for Natural Gas Loans

Jesús Fernández Cruz[a], **Carlos Ignacio Hernández Castellanos**[a]

[a]Research and Technology
Mutuo Financiera
Juan de la Barrera 50, Condesa, Cuahtémoc, C.P. 06140, Mexico City, Mexico
jfernandez@mutuofinanciera.com, carlos@mutuofinanciera.com

Mutuo Financiera grants credits and leases for new natural gas vehicles as well as to transform old vehicles to natural gas. At this moment Mutuo has operations in 6 states of Mexico, each of them with different characteristics, needs, and risk. Thus, it is highly essential to have collocation and risk management strategies to decide which credits we would need to approve in order to maximize profit.
The objective of this work is to design and develop a module for the many-objective portfolio optimization problem coming from natural gas credits. In particular, we are interested in: maximizing IRR and coverage; minimizing term, loan-to-value, risk and minimize CO_2 emissions. The last objective is important since the conversion to natural gas has an impact to the environment because natural gas is up to 60% cleaner than gasoline.
In this work, we will show the first steps towards the modeling of the problem. In particular, a statistical analysis of the behavior of the natural gas consumers. Such as daily consumption, the number of chargers per week, behavior along the different year seasons, among others. Finally, we will discuss some perspectives that will lead to a natural gas consumption model.

On the Design of Hybrid Evolutionary Multi-objective OptimizationAlgorithms for Constrained MOPs

Oliver Schütze[a], **Adriana Lara**[b], **Lourdes Uribe**[b], **Fernanda Beltrán**[a]

[a]Computer Science Department
Cinvestav-IPN
Mexico City, Mexico
schuetze@cs.cinvestav.mx, mbeltran@computacion.cs.cinvestav.mx

[b]Mathematics Department
ESFM-IPN
Mexico City, Mexico
adrianalaraesfm@gmail.com,l.uriberichaud@gmail.com

Evolutionary multi-objective optimization is a story of huge success which has a huge impact in finance and industry. However, until now such multi-objective evolutionary algorithms (MOEAs) need quite a few function evaluations to obtain acceptable Pareto set/front approximations. One remedy to overcome this problem is to hybridize MOEAs with local search. If the local search is coming from classical mathematical programming gradient information is used which leads to a relatively high cost. This cost is even increasing in case the multi-objective optimization problem (MOPs) is complex (e.g. highly constrained) since then the probability that a local search from an initial point leads to an optimal solution is low.
In this talk we first consider the effect of multi-objective stochastic search (MOSLS) within MOEAs. We will show that both pressure toward and along the Pareto set is already inherent in MOSLS for unconstrained MOPs which describes on facet of the huge sucess of MOEAs. In a next step, we will develop generational operators to obtain a pressure toward and along the Pareto front for constrained problems. The particularity of the subspace polynomial mutation (SPM) operator is that it does not explicitly compute the gradients but extracts this information in a best fit manner out of the current population of the MOEA.
We conjecture that these tools will allow for the fast an reliable treatment of complex MOPs with we demonstrate on some first numerical results.

An overview of constraint handling methods for MOPs.

Lourdes Uribe[a], **Adriana Lara**[b] and **Oliver Schütze**[b]

[a,b]Escuela Superior de Física y Matemáticas.
Instituto Politécnico Nacional.
Av. Instituto Politécnico Nacional, Edificio 9, Gustavo A. Madero,
Lindavista, 07738 Ciudad de Mexico.
[a]l.uriberichaud@gmail.com, [b]adriana@esfm.ipn.mx

[c]Computer Science Department
CINVESTAV-IPN
Av. IPN 2508, C. P. 07360, Col. San Pedro Zacatenco, Mexico City, Mexico
[c]schuetze@cs.cinvestav.mx

Multiobjective Optimization Problems arise in a natural way in diverses knowledge areas. In general, optimization seeks to obtain a greater benefit through the resources that are available. Therefore, when modeling a Multi-objective Optimization Problem (MOP), it is important to consider the problem limitations and add constraints to the model. In latest years, Multi-objective Evolutionary Algorithms (MOEAs) have been applied to solve MOPs. Nevertheless, in evolutionary computing few research has been conducted in Constrained Multi-objective Optimization (CMO). The most common approach is using penalty methods[JD14, WYT09]. In this type of methods, infeasible individuals are penalize based on their objective value and constraint violations. In this talk we give an overview of our recently proposed constraints handling methods[LUAea18]. This methods have specific mechanisms that deal with the constraints in a wiser way. The first one (SPM) is a novel mutation operator that takes advantage of feasible subspaces and effectively explore search regions on constrained MOPs. This feasible subspace is computed using neighborhood information of the mutation candidate. And the second one (GFDD) is a new gradient free descent direction for constraint Bi-objective Optimization Problem (BOP). This descent direction is approximated via neighborhood information of a solution. Both of them work inside different Multi-objective Evolutionary Algorithms (MOEAs). Numerical results indicate that these ideas yield to competitive results in several cases.

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VHDL by MOEA: a tool for Multi-objective Optimization in High-Level Synthesis

Darian Reyes Fernández de Bulnes[a], Yazmin Maldonado[b]

[a]Department of Electrical and Electronic Engineering
Posgrado en Ciencias de la Ingeniería
Instituto Tecnológico de Tijuana
Tijuana, Baja California, Mexico
darian.reyes@tectijuana.edu.mx

[b]Department of Electrical and Electronic Engineering
Posgrado en Ciencias de la Ingeniería
Instituto Tecnológico de Tijuana
Tijuana, Baja California, Mexico
yaz.maldonado@tectijuana.edu.mx

The Field Programmable Gate Array (FPGA) has become increasingly popular in different areas of knowledge. High-Level Synthesis (HLS), also known as Behavioral Synthesis, is the process of transform algorithmic description to synthesizable Register Transfer Level (RTL) netlist into electronic devices such as FPGAs. HLS allows designers to work at a higher-level of abstraction by using a software to define the hardware behavior. Inside this process, there are several opportunities to perform optimizations during the scheduling, allocation, and binding of a circuit design. The scheduling defines how all design's operations will be scheduled into clock cycles. The allocation determines the type and the number of hardware resources (for instance: functional units, storage, or connectivity components) needed to satisfy the design's constraints. The binding determines how each variable (carried out values across clock cycles) will be bound to a storage unit [2]. These optimizations are highly multi-objective by nature, with compromise between objective functions, such as, delay, area, and power [1]. For the optimization of several objective functions at the same time, it is necessary to apply Multi-Objective Evolutionary Algorithms (MOEAs).
In the last ten years, several efforts have been made to create software tools for HLS containing multi-objective optimizations [3]. However, those proposals have many limitations, mainly because they focus on being an Electronic Design Automation (EDA) tool, and not in the performance of the optimization. Some of these limitations are: a bit possibility in the variation of the multiobjective optimization algorithm and its parameters, lack of charts about the optimization process to find details of interest, no access to the Pareto Front in order to the designer can choose which solution is going to implement in an FPGA, and that the optimization process is executed on the user side, instead of in an online server with high potential for computing and parallelization.
To overcome these limitations, we are developing *VHDL by MOEA*, an academic software approach to apply MOEAs for simultaneous minimization of delay, area, and power during HLS process. *VHDL by MOEA* has as input a VHDL code with the behavioral description to be implemented. As output, the optimized VHDL code is obtained. To achieve this, the software has four general modules that communicate with each other. In the first module the compile task is done, the input VHDL code is syntactically validated and it is converted to Data Flow Graph (DFG) using the libraries Flex and Bison. The second one is capable of performing the multi-objective optimization on the DFG with the MOEAs NSGA-II, NSGA-III and SPEA2 with a multi-chromosome representation. The third module converts the optimized DFG in RTL written in VHDL code, this output VHDL code is a Finite State Machine design and it is ready to be implemented into the FPGA device with an EDA tool like a Vivado by Xilinx. The function of the fourth module is controlling the three previous modules and create an automated process for the designer. This last module is web-based with a Model-View-Controller architecture. The first three modules are written in C++ language and the fourth one in Python. MySQL database is used and data exchange is

done in JSON and XML formats. The Figure 1 is shown the proposal diagram with main modules and data dependence between them.
Even though this tool is still under construction, we have already been able to verify its performance by basic test cases. This work is an extension of several previous publications [5, 4, 6], where the main algorithms of the process were subjected to experiments.

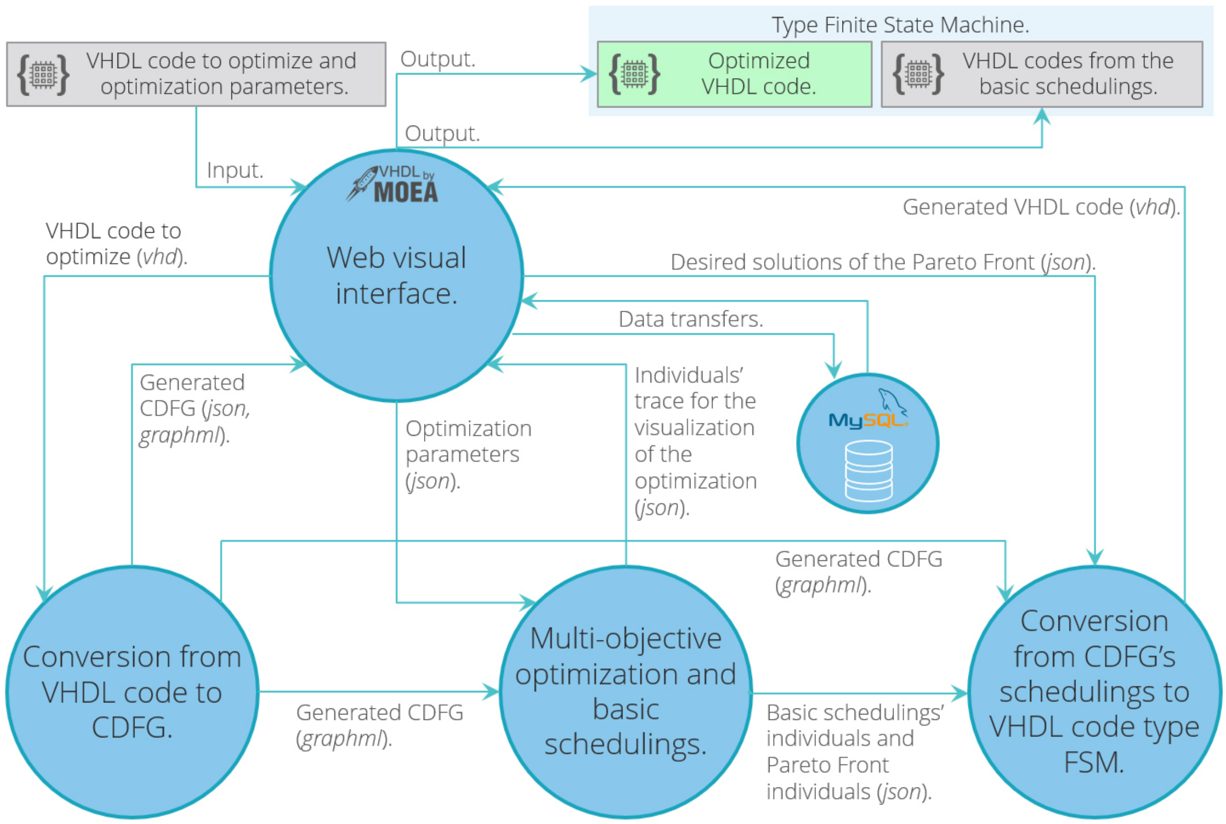

Figure 1: Implementation proposal diagram

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Using the Pareto Explorer Framework for the Decision-making Processes in Real-world Applications

Oliver Cuate[a] and **Oliver Schütze**[b]

[a,b]Computer Science Department
CINVESTAV-IPN
Av. IPN 2508, C. P. 07360, Col. San Pedro Zacatenco, Mexico City, Mexico
[a]ocuate@computacion.cs.cinvestav.mx, [b]schuetze@cs.cinvestav.mx

In many real-world applications, the problem arises that several objectives have to be optimized concurrently, leading to a multi-objective optimization problem (MOP). In recent years, the applications are getting more and more complex, in particular, the number of objectives involved in the models has increased. The term many objective optimization problems (MaOPs) is used for problems with more than 4 objectives, which play an important role in optimization and in many decision-making processes.
Multi-objective evolutionary algorithms (MOEAs) have recently caught the interest of many researchers. One of the principal advantages of this kind of algorithms is that they compute a finite size approximation of the entire Pareto set in one single run of the algorithm. However, it is known that the solution set of this kind of problems, the Pareto Set, typically forms a $(k-1)$-dimensional object, where k is the number of objectives. Due to this fact, it is computationally expensive to approximate the entire Pareto set. Hence, the use of MOEAs is not effective to solve MaOPs.
On the other hand, classical mathematical programming techniques are capable of quickly detecting Pareto optimal solutions regardless of the dimension of the problem (both in decision space of the problem and in the number of objectives). However, such methods will by construction only find *one* optimal solution per run, and it is unclear if this solution is exactly what the decision maker is looking for.
As an alternative, we propose the Pareto Explorer framework (PE), which has been conceived as global/local exploration tool for the efficient numerical treatment of MaOPs. In a first step, an optimal solution is computed via a global search algorithm where users preferences are included as good as possible (e.g. via a reference point method). Then, in a second step, the obtained solution will be refined in an interactive procedure with the decision maker according to his/her preferences.
In this talk, the most important details of the PE are presented, as well as its application and effectiveness in some benchmark problems and in two real-world applications; the former is related to industrial washing machines, and the latter is about a model of the plastic injection process.

Variation Rate: an Alternative to Maintain Diversity in Decision Space for Multi-objective Evolutionary Algorithms

Oliver Cuate[a] and Oliver Schütze[b]

Computer Science Department
CINVESTAV-IPN
Av. IPN 2508, C. P. 07360, Col. San Pedro Zacatenco, Mexico City, Mexico
[a]ocuate@computacion.cs.cinvestav.mx, [b]schuetze@cs.cinvestav.mx

In almost all cases the performance of a multi-objective evolutionary algorithm (MOEA) is measured by the quality of its approximation in objective space. As a consequence, most MOEAs focus on such approximations while neglecting the distribution of the individuals in decision space. This, however, represents a potential shortcoming in certain applications as in many cases one can obtain the same –or a very similar– quality in objective space with very different solutions in decision space. This kind of solutions could be very valuable information, for the decision maker, for the realization of the project.
In this work, we propose the variable-NSGA-III (vNSGA-III) an algorithm that performs an exploration both in objective and variable space. The idea behind this algorithm is the so-called variation rate, a parameter-free heuristic that can be easily integrated into other MOEAs. We demonstrate the effectiveness of our approach on several benchmark problems, where we show that, compared to other methods, we significantly improve the quality of the approximation in decision space without losing quality of the approximation in objective space.

DPEM-HH: A population evolvability-based multi-objective hyperheuristic to solve dynamic multi-objective optimization problems

Teodoro Macias-Escobar[a], Laura Cruz-Reyes[a], Bernabé Dorronsoro[b]
Héctor Fraire-Huacuja[a], Claudia Gómez-Santillán[a]
Nelson Rangel-Valdez[a], Daniel Martínez-Vega[a]

[a]Division of Graduate Studies and Research
Tijuana Institute of Technology
Tijuana, Mexico
teodoro_macias@hotmail.com

[b]Department of computer engineering
Cadiz University
Cadiz, Spain
bernabe.dorronsoro@uca.es

Hyper-heuristics are methodologies that can use several heuristics or meta-heuristics, defined as low-level heuristics (LLHs), to solve a problem. This process combines the strength of those heuristics in an attempt to produce a better solution than said heuristics could archive working separately. This concept has brought interest among researchers, as it provides another option to solve optimization problems. However, to our knowledge, hyper-heuristic strategies based on the properties of a dynamic optimization problem and an optimization algorithm set applied to solve it have not been studied yet.
Population evolvability is a fitness landscape analysis method that evaluates the properties of an optimization problem based on the capability and probability of an algorithm used to solve it to improve its current population [1]. Based on this concept we propose in this paper the Dynamic Population-Evolvability based Multi-objective Hyper-heuristic (DPEM-HH). A hyper-heuristic to solve dynamic multi-objective optimization problems (DMOPs) using dynamic multi-objective optimization evolutionary algorithms (DMOEAs), as its set of available LLHs.
DPEM-HH uses three versions of DNSGA-II [2] as LLHs in this paper. Each version has a different change adaptation method which consists of replacing a certain percentage of the current population with new random solutions, mutations of current solutions or the combination of both methods.
This paper presents two hyper-heuristic selection methods. The first method uses population evolvability to select which LLH will be used for the next time step (DPEM-HH PE). The second method combines this value with a set of performance metrics using a choice function based on [3] to perform a selection process (DPEM-HH CF).
The optimization process of DPEM-HH is performed following these steps: i) The first time step is solved using NSGA-II, as the environment has not changed yet; ii) When a change in the problem is detected, all LLHs are executed for a set of test generations using the current population; iii) The obtained results are compared and a selection method chooses which LLH to apply until another problem change is detected.
DPEM-HH is tested on several DMOPs from the FDA [4], DMZDT [5] and dMOP [6] benchmark functions, the change severity for FDA and dMOP instances are set to 10 and to 100 for DMZDT instances. The landscape change frequency is set to 25 generations for all instances. The three DNSGA-II versions, both when run individually or used as an LLH, have a population size of 100. Simulated binary crossover and polynomial distribution are used as crossover and mutation operators respectively [7]. The crossover and mutation probability of each DMOEA are set in 0.9 and $1/n$, let n be the number of variables of a DMOP, respectively. Distribution indexes are set on 10 for crossover and 20 for mutation.
The performance metrics selected to be used in the choice function are the ratio of non-dominated solutions (RNI) [8], inverted generation distance (IGD) [9], maximum spread (MS) [10] and hypervolume ratio (HV-

Ratio) [11]. These set of metrics allow the function to evaluate the convergence and diversity of the solutions obtained by all tested algorithms.
The solutions obtained by DPEM-HH are compared with the results obtained by each version of DNSGA-II used as an LLH run individually. The set of metrics that were used in the choice function previously mentioned are used to evaluate the performance of all algorithms. Table 1 summarizes some of the obtained results for the DMZDT1 test instance. For almost all instances, DPEM-HH has at least one variant that outperforms DNSGA-II. Also, DPEM-HH variants significantly outperform all tested DNSGA-II variants for IGD, MS and HV-Ratio. This demonstrates that DPEM-HH takes advantage of its designed methodology by using all available DMOEAs cooperatively. Combining their strengths while covering their flaws.

Table 1: Mean and standard deviation for DPEM-HH and DNSGA-II for DMZDT1

Algorithms	RNI	IGD	MS	HV-Ratio
DPEM-HH PE	9.880E-1(1.098E-3)	4.687E-3(8.80E-5)	9.700E-1(1.644E-3)	9.025E-1(1.020E-3)
DPEM-HH CF	9.883E-1(1.293E-3)	4.675E-3(8.40E-5)	9.705E-1(1.686E-3)	9.027E-1(8.480E-4)
DNSGA-II	9.875E-1(1.452E-3)	4.833E-3(1.83E-4)	9.691E-1(3.825E-3)	8.987E-1(1.508E-3)

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A Neural Network-Evolutionary Computation Framework for Remaining Useful Life Estimation

David Laredo[a], **Zhaoyin Chen**[a], **Oliver Schütze**[b], **Jian-Qiao Sun**[a]

[a]Department of Mechanical Engineering
University of California, Merced
5200 Lake Road, Merced, Ca.
jsun3@ucmerced.edu

[b]Department of Computer Science
CINVESTAV
Av. IPN, La laguna Ticoman, Ciudad de Mexico.
schuetze@cs.cinvestav.mx

This paper presents a data-driven framework for estimating the remaining useful life (RUL) of mechanical systems. Two major components make up the framework: a multi-layer perceptron as base regressor and an evolutionary computation algorithm for the tuning of data-related parameters. On the data side, the framework makes use of a strided time window along with a piecewise linear model to estimate the RUL label for each time window within the training sets. Tuning the data-related parameters using the optimization framework here presented allows for the use of simple regressor models, e.g. neural networks with few hidden layers and few neurons at each layer, which can in turn be deployed in environments with very limited resources such as embedded systems. The proposed method is evaluated on the publicly available CMAPS dataset. The accuracy of the proposed method is compared against other state-of-the art methods available in the literature and it is shown to perform better while making use of a simpler, compact model.

Transfer Learning of Evolved Feature Transformations

Luis Muñoz[a], **Leonardo Trujillo**[a], **Sara Silva**[b]

[a]Tree-Lab, Doctorado en Ciencias de la Ingeniería, Departamento de Ingeniería Eléctrica y Electrónica
Instituto Tecnológico de Tijuana
Blvd. Industrial y Av. ITR Tijuana S/N, Mesa Otay C.P. 22500, Tijuana BC, México
lmunoz@tectijuana.edu.mx, leonardo.trujillo@tectijuana.edu.mx

[b]BioISI - Biosystems & Integrative Sciences Institute, Departamento de Informática
Faculdade de Ciências, Universidade de Lisboa
Universidade de Lisboa, 1749-016 Lisboa, Portugal
sara@fc.ul.pt

Abstract

Transfer Learning (TL) in Genetic Programming (GP) is seen as something unlikely since solutions are seen as defined by the input data for a specific problem. If we consider GP it is difficult to imagine a possible way to transfer knowledge found by evolution because trees are assumed to be performing highly specialized feature construction and model fitting within a single tree. Therefore it is necessary to separate features construction and solution modeling in the evolutionary cycle. GP is well known for the ability to work with multiple kinds of building blocks for feature construction. On the other hand GP tends to have problems tunning final solution models that are represented as a single tree. It is therefore desirable to let GP handle feature construction and an independent learning method handle model fitting to guide evolutionary search. In such scenario, it may be possible to transfer evolved feature transformation operators between domains, and then perform model fitting without any need for further evolution, this is the core idea in TL. This work presents initial results of applying TL to a GP-based feature transformation method called M3GP that produces models that are linear in parameters based on non-linear feature transformations. Results show that it is indeed possible to use TL in such a GP system.

A method to optimize the Order Type Maximal Perturbation through multiple single point displacements

Heriberto Cruz Hernández and Luis Gerardo de la Fraga

Computer Science Department, Cinvestav
Av. IPN 2508, 07360 Mexico City, México
fraga@cs.cinvestav.mx

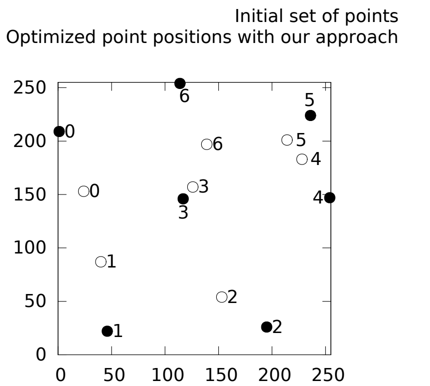
We propose in this work a method to optimize the Maximal Perturbation (MP) associated to the Order Type (OT) of a given set of points C in $\mathbb{R}^2$. The OT describes a set of points in terms of each of its triplets orientations. This OT is represented by the so-called $\lambda-$matrix, which can be used as a descriptor of C, and this descriptor is invariant to rotations, translations, scaling and perspective orientations of the point set C [1].

For each set of points in $\mathbb{R}^2$ with no collinear points there exists an associated OT represented by its $\lambda-$matrix. Given a set of points C_1, with λ_1 as its λ-matrix, which could be affected by noise in its point positions to obtain a new set C_2. The triplets orientations of C_2 could change in such way that λ_1 will no longer describe C_2.

The maximal noise that can be added to any of point in C without changing its OT is called the maximal perturbation MP(C) [1]. The maximal perturbation is defined as the half of the minimal distance from any point $\boldsymbol{p}_i \in C$ to any line defined by a pair of points $\overline{\boldsymbol{p}_j, \boldsymbol{p}_k}$ in C with $i \neq j \neq k$. A greater value MP(C) allows more noise in the point positions in the elements of C without changing its OT.

We propose a method to optimize the positions of the points in C to increase the value of MP(C). We perform multiple single points displacements to the points in C to obtain C', such that $\lambda(C) = \lambda(C')$ and $\mathrm{MP}(C') \geq \mathrm{MP}(C)$ with each displacement. After multiple points displacements, and when no more changes can be performed, a new set with greater maximal perturbation is obtained. To test our approach we optimize the MP of each set of points of an existing OT database in the literature [2]. In Fig. 1 we show an instance of the results obtained with our approach, in the figure the resulting set of points is described by the same $\lambda-$matrix but it has a higher MP value.

The optimized set of points can be used to construct more robust fiducial markers for Computer Vision applications. An augmented reality application that uses this kind of markers will be shown.



$$\lambda = \begin{bmatrix} - & 5 & 4 & 3 & 2 & 1 & 0 \\ 0 & - & 5 & 2 & 4 & 3 & 1 \\ 1 & 0 & - & 2 & 5 & 4 & 3 \\ 2 & 3 & 3 & - & 3 & 2 & 2 \\ 3 & 1 & 0 & 2 & - & 5 & 4 \\ 4 & 2 & 1 & 3 & 0 & - & 5 \\ 5 & 4 & 2 & 3 & 1 & 0 & - \end{bmatrix}$$

Figure 1: Left: The initial and the optimized set of points, with MP equal to 5.44 and 16.61, respectively. Right: the associated and unchanged $\lambda-$matrix for both set of points. MP is given in the arbitrary units in the graph.

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Depth estimation for a monocular vision system

Saúl Martínez Díaz[a], **Maarouf Saad**[b], **Jawhar Ghommam**[c]

[a]División de Estudios de Posgrado e Investigación
Tecnológico Nacional de México, Instituto Tecnológico de La Paz
La Paz, BCS
saulmd@itlp.edu.mx

[b]Département de Génie Électrique
École de Technologie Supérieure
Montréal, Canada
Maarouf.Saad@etsmtl.ca

[c]Department of Electrical and Computer Engineering
College of Engineering, Sultan Qaboos University
Al Khoudh, Oman
jawhar.ghommam@gmail.com

Depth estimation in real world scenes is an important topic in several applications such as navigation of autonomous robots, simultaneous localization and mapping (SLAM) and augmented reality. Even though there is technology for this purpose, in some cases, this technology has some disadvantages. For example, GPS systems are susceptible to interference, especially in places surrounded by buildings, under bridges or indoors; alternatively, RGBD sensors can be used, but they are expensive, and its operational range is limited. Monocular vision is a low-cost suitable alternative that can be used indoor and outdoor. Besides, many mobile devices include at least one camera sensor.

In this work, we propose an algorithm to compute depth from two views of at least three 3D points fixed on real world, captured with a calibrated camera. These points can be obtained from any object with known dimensions. In order to compute depth, the algorithm requires to solve a nonlinear equation system obtained from Euclidian distances between points pairs; for that purpose, we use a numerical method based on gradient descent. We tested the proposed algorithm and compared results with those obtained from a Kinect device.

Dynamical and Numerical Analysis of Chen Chaotic Oscillator

V. A. Adeyemi[1], A. Bonilla-Rodriguez[1], R. Y. Serrato Andrade[1], G. Entrambasaguas-Leon[1], Y. Sandoval-Ibarra[2], E. Tlelo-Cuautle[3], J. C. Núñez-Perez[1]

[1] Instituto Politécnico Nacional, IPN-CITEDI, Av. Instituto Politécnico Nacional No. 1310, Col. Nueva Tijuana, Tijuana, Baja California, México. C.P. 22435.
[2] Tecnológico Nacional de México, Instituto Tecnológico de Tijuana, Blvd. Industrial s/n, Cd. Industrial, Tijuana, Baja California, C.P. 22430.
[3] Instituto Nacional de Astrofísica, Óptica y Electrónica, INAOE, Luis Enrique Erro # 1, Tonantzintla, Puebla, México C.P. 72840.
nunez@citedi.mx

Abstract. The study of non-linear dynamics has given rise to a whole new perspective known as chaos. As a matter of fact, chaos has become an important research topic in the last few decades. The concept of chaos was first studied by Henri Poincaré, a French mathematician between 1887 and 1890. He was the first to point out that many deterministic systems display a sensitive dependence on initial conditions. Chaos theory, also known as the “Butterfly Effect”, has applications in several sectors such as telecommunication, engineering, medicine, transportation and many more. Chaotic phenomenon is found in many natural and artificial systems, such as weather and road traffic respectively. In essence, chaos has basic properties among which are aperiodic movements, deterministic and sensitivity to initial conditions. Chaos has oscillating movements because the trajectories do not fit a fixed point, periodic orbit or quasi-periodic orbit. It is deterministic because the system is not random, i.e. the irregular behaviour of chaotic system is as a result of its inherent nonlinearity. Chaos is sensitive to initial conditions because very similar initial conditions produce different behaviours in the trajectories after a long enough time. That is, trajectories beginning with very close initial conditions eventually separate exponentially. This particular property makes long-term prediction of chaos impossible. There are many chaotic oscillators which generate chaos either in scroll or wing form. In this paper, the Chen chaotic system was studied. The work includes the mathematical and numerical analysis of Chen oscillator by means of equilibrium points, eigenvalues, and Lyapunov exponents to examine the basic dynamic properties. The eigenvalues obtained show that the Chen oscillator is unstable at the equilibrium points examined while the maximum Lyapunov exponent obtained confirms its chaotic nature. Also, the bifurcation diagrams show the stability of the Chen system with the three system parameters. The results show that bifurcation with parameter b gives the longest period of stability.

Keywords: Chaos, Chen Oscillator, Mathematical and Numerical Analysis, Lyapunov Exponent, Stability.

IMPLEMENTATION OF AN OBJECT RECOGNITION SYSTEM BASED ON DEEP LEARNING IN A RPAS

Jesus Antonio Alvarez-Cedillo [a], Teodoro Alvarez-Sanchez[b], Jacobo Sandoval Gutierrez[c]

[a]Instituto Politenico Nacional
UPIICSA
Av te 950 Col. Granjas Mexico, CDMX
jaalvarez@ipn.mx

[b]Instituto Politenico Nacional
CITEDI
Av IPN 1310 Col. Nueva Tijuana, Tijuana
talvarez@citedi.mx
[c]Universidad Autonoma Metropolitana
Lerma
Av. Hidalgo Poniente 46, La Estacion, 52006 Lerma de Villada, Estado de Mexico, MEXICO
jacobosandoval@correo.ler.uam.mx

One of the critical fields of Robotics and Artificial Intelligence is the Computer Vision; it consists of robotic systems that can recognise and understand images and scenes, it is generally composed of the following areas: image recognition, object detection and generation of images. The detection of objects is probably the most profound aspect of robotics because of the importance and a large number of applications that can be developed. However, Deep learning, in turn, provides excellent potential by exploiting optimal training with the speed and simplicity of learning, where the primary challenge in robotics is to use embedded systems to perform this task. In this article we show the successful implementation of equipping in an aerial system manned by remote control (RPAS) in the NVIDIA Jetson TX development kit card, using a successful method of object recognition based on focal loss and the results , the challenges faced by software developers and the final solution provided.

Keywords: RPA, UAV, RPAS, UAS, drone, computer vision, object detection, modern methods of object detection.

REAL-TIME WEAPON RECOGNITION USING DEEP LEARNING

Jesus Antonio Alvarez-Cedillo [a], Teodoro Alvarez-Sanchez[b], Jacobo Sandoval Gutierrez[c]

[a]Instituto Politenico Nacional
UPIICSA
Av te 950 Col. Granjas Mexico, CDMX
jaalvarez@ipn.mx

[b]Instituto Politenico Nacional
CITEDI
Av IPN 1310 Col. Nueva Tijuana, Tijuana
talvarez@citedi.mx
[c]Universidad Autonoma Metropolitana
Lerma
Av. Hidalgo Poniente 46, La Estacion, 52006 Lerma de Villada, Estado de Mexico, MEXICO
jacobosandoval@correo.ler.uam.mx

Determine if a person is a carrier of weapons in a public place is currently an intelligence goal and high priority of various countries before the threat of terrorist acts or emotionally unstable people. The use of technology can be used to recognise patterns of different types of weapons. However, the recognition and classification of images in traditional methods of the field of computer vision require a broad base of training images or videos, a team of considerable computing capacity and much time to carry out the training but there are still several detection problems. The use of deep learning allows increasing the effectiveness in the detection of patterns for its application which significantly outperform other solutions in multiple domains and positions deep learning as an essential option in the development of algorithms for natural language, vision by computer and robotics and game development. Also, it reduces the need to characterise the elements or points to be analysed carefully, which reduces time. In this article, we show the development of a real-time recognition algorithm for detected weapons with the use of a high-definition camera (4K), implemented in an NVIDIA Jetson TK1. The proposed algorithm showed greater effectiveness in detecting different types of weapons such as pistols, machine guns and assault rifles.

Keywords: computer vision, object detection, modern methods of object detection, deep learning, real-time applications.

Probabilistic Uniformity as a Similarity Measure Robust to Lighting Changes

Alejandro Martin Gomez [a], Javier Flavio Vigueras Gomez [b]

[a]Department of Informatics
Technical University of Munich
Boltzmannstr. 3, 85748 Garching
email

[b]Facultad de Ciencias
Universidad Autonoma de San Luis Potosi
Av. Salvador Nava s/n, Zona Universitaria Poniente 78290, San Luis Potosi
javier.vigueras@uaslp.mx

This work presents an algorithm capable of estimating geometric and radiometric transformation variations between pairs of images obtained either by a stereo pair or by a monocular camera translating in a video sequence, despite of projective geometric changes and non-linear radiometric variations observed between the bidimensional images of a three-dimensional scene.

The algorithm proposed in this work makes use of an alternative similarity measure based in the Probabilistic Uniformity, instead of the state-of-art Mutual Information approach which has demonstrated to be robust against geometric changes, non-linear radiometric variations and even to a certain level of occlusions. The probabilistic uniformity represents a not so computationally expensive alternative when a second order derivative optimization (quai-Newton) method is used and presenting a similar performance as the one observed by using a Mutual Information approach.

This algorithm allows to estimate the parameters that modify small regions of interest, selected from one of the images obtained from a scene in a two view geometry perspective, to make them match with the geometric changes despite radiometric variations observed in the same regions at a second image of the scene.

Keywords: non-linear optimization, tracking, similarity measures, mutual information, probabilistic uniformity.

Improving a vision-based SLAM system using Novelty Search

Víctor R. López-López[a], **Leonardo Trujillo**[a] and **Pierrick Legrand**[b]

[a]Departamento de ingeniería eléctrica y electrónica, posgrado en ciencias de la ingeniería
Instituto Tecnológico de Tijuana
Blvd. Alberto Limón Padilla y Av. ITR, Tijuana, Baja California, México
vlopez@tectijuana.edu.mx, leonardo.trujillo @tectijuana.edu.mx

University of Bordeaux & Institute of Mathematics, Bordeaux, France
IMB UMR CNRS 5251 & Inria Bordeaux Sud-Ouest, France
pierrick.legrand@u-bordeaux.fr

Vision-based SLAM has produced a large amount of theoretical and practical systems for real-world applications, that achieve impressive results in many domains. Nonetheless, there are still areas for improvement, particularly in managing what can be called the efficiency and accuracy tradeoff of a given SLAM implementation. This has lead some to develop specialized tools for benchmarking, such as SLAMBench, that can provide a detailed characterization of the behavior of a SLAM system, based on both functional and non-functional properties. However, the improvement of the system is a difficult task, as any other implementation, it involves human programming experts to solve this problem and the degree of difficulty increases with the number of properties to improve; this approach is typically handled by a team of human programmer's, and it is known to be time-consuming, tedious and expensive. Another and recent approach, is to automate as much of the improvement process as possible; this is the goal of Genetic Improvement (GI), which performs a search at the level of source code to find the best variant of a baseline system that improves non-functional properties while maintaining functionality, with noticeable results in several domains. There a many aspects of this automated approach that are currently being explored.

In particular, this work deals with two key points: the first is the improvement of a popular SLAM system, KinectFusion, using a GI framework, GISMOE, to reduce the execution time (EXT) while maintaining and absolute trajectory error (ATE); the second is to deal with the issue of efficiently exploring the search space of possible software versions in which GI operates, the proposal is to integrate Novelty Search (NS) within the GISMOE GI framework to improve KinectFusion; in both, we use the SLAMBench benchmarking tool as an objective function, in order to pose a supervised learning problem and explore the algorithmic design space of KinectFusion. The results indicate that it is feasible to automatically improve KinectFusion by reducing both EXT and ATE of KinectFusion using a standard set of benchmarking video sequences for both testing and training. Moreover, NS with GISMOE is able to explore more parts of the search space and find a better solution than GISMOE alone. In the case of using GISMOE alone, average improvement over 21 trajectories are 17% and 2.4% for EXT and ATE; in the case of GISMOE with NS, the average improvement is 37% and -11%. The resulting averages in ATE can be neglected and considered both of them zero because they mean a difference in millimeters. With this consideration, the best solution was found by GISMOE with NS.

A review in autonomous driving: present and future trends

América Berenice Morales Díaz
researcher at the Robotics and Advanced Manufacturing
Cinvestav Saltillo
america.morales@cinvestav.edu.mx

Abstract.
Autonomous driving vehicles represent a mature work technology with potential to diminish traffic and to enhance safety, accessibility, efficiency, and convenience of vehicles transportation. Nowadays, the computational and sensing advances in the car allow the users to obtain information about its state in real time. The future vehicles cannot only be capable to obtain their own information and from their environment, but also to share it among others vehicles to obtain reliable information about traffic conditions and to develop safe driving policies. In the present review an autonomous driving and decision-making is provided, and the work developed in the motion planning and feedback control low labels at the Robotics and Advanced Manufacturing Group is also presented.

A study of the effect of the decision maker profile in the decision-making process

Mercedes Perez-Villafuerte[a], **Laura Cruz-Reyes**[b], **Nelson Rangel-Valdez**[b]
Claudia Gomez-Santillan[b], **Hector J. Fraire-Huacuja**[b], **Ma. Lucila Morales-Rodriguez**[b]
Alejandro Estrada-Padilla[a]

[a]Department of Computing Science
Tijuana Institute of Technology
Calzada del Tecnologico, Fraccionamiento Tomas Aquino, Tijuana, Mexico
pvmercedes@gmail.com

[b]Department of postgraduate and investigation studies
Technological Instutite of Madero City
Juventino Rosas 114, Los Mangos, Madero City, Mexico
cruzreyeslaura@itcm.edu.mx

Abstract
One of the promising variants in the decision-making process is the incorporation of preferences using the a priori methodology, which has the advantage of delimiting the search space for an optimal solution. However, the specialized literature is based on arbitrary reference sets, which are examples of random solutions. In this paper, it is proposed that these sets of references are associated with profiles that characterize decision makers. As part of the proposed solution, it is presented a modularized architecture called P-HMCSGA for multicriteria optimization with preferences satisfaction specified in a preferential profile. P-HMCSGA consists of three phases: it initiates with the generation of a reference set for a specified profile, then follows the transformation of these indirect preferences into parameters of a preferential model [1] using a methodology of Preference Disaggregation Analysis (PDA) [2]. Finally, these preferences are incorporated into the search process of a multiobjective optimization algorithm [3].

In this paper, is studied the effect of the profile of a decision maker in the search process. As part of the study, there are introduced three preferential profiles that represent some characteristics of the decision maker. These profiles are described below and are proposed as a case of study to validate the proposed architecture:

- *Established projects*: A predefined set of projects are considered in the portfolio to be formed. One possible reason for this preference is that these projects were profitable in the past.
- *Preference in area or region*: It is considered a priority to give preference to portfolios that contain more projects that support an established area or region.
- *Cardinality*: This profile favor portfolios in which the number of supported projects is maximized.

The main interest of this study is to analyze if there is a change in the solutions obtained by allowing the decision maker to express their preferences in these profiles, and how these are transformed into parameters of a preferential model by characterizing it according to some profile. In order to execute the experiment, instances of the public portfolio problems were used as a case of study in medium and large scale. The results obtained in the experiments carried out with these instances are explained with amplitude, it is worth mentioning that only the results of an instance are shown since the behavior presented in these results were replicated in all the evaluated instances.

Table 1 shows a summary of the results for a tested instance of 9 objectives and 150 projects, where the maximum number of projects found for the cardinality profile is 77, for stablished projects profile is 15 and

for the profile with preference in area or region is 34. Table 1 shows, within parentheses, the value found for the analyzed profile, and before the parenthesis, it is written the number of solutions that obtained that value.
It can be observed that the highest number of solutions found just coincides with the diagonal. The result of these experiments is promising, it was observed that the most satisfactory solutions are obtained using parameters that were obtained specifically for that profile during the search. As a corollary, the set of solutions for one profile may not be satisfactory for the specifications of another profile.

Table 1: Evaluation of three preferential profiles in a set of solutions

Configuration of parameters	Evaluation in the profile		
	Cardinality	Established projects	Preference in area or region
Cardinality	314 (77)	32 (15)	5 (32)
Established projects	20 (77)	136 (15)	2 (32)
Preference in area or region	179 (77)	0 (15), 32(11)	1(34), 5(33), 35(32)

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Obtaining inference rules through compensatory fuzzy logic for decision problems with imperfect knowledge

Gabriela Salas-Tovar[a], **Claudia G. Gomez-Santillan**[b], **Laura Cruz-Reyes**[c]
Hector J. Fraire-Huacuja[d], **Alejandro Estrada-Padilla**[e]
Nelson Rangel-Valdez[f]

[a,b,c,d,e]Department of Posgraduate and Investigation studies
National Mexican Institute of Technology, Madero Institute of Technology
Av. Primero de Mayo 1610, Los Mangos, 89460 Cd Madero, Tamps.
[a]6abi.sg@gmail.com, [b]cggs71@hotmail.com, [c]lauracruzreyes@itcm.edu.mx
[d]hector.fraire2014@gmail.com, [e]aestrada1993@hotmail.com

[f]CONACYT
National Mexican Institute of Technology, Madero Institute of Technology
89440 Tamaulipas, Mexico
nrangelva@conacyt.mx

In daily life it is necessary to make decisions, these situations are known as decision problems. In computer science, different algorithms have been proposed to solve this type of problems, which are regulated by a set of parameters, to achieve a faithful problem representation and effectiveness in solving the problem.

In this paper a decision problem solution is approached through an adaptative parameter adjustment applying fuzzy logic. In this reggard the inference rules which implement compensatory fuzzy logic, are necessary.
A fuzzy system structure is constituted by three main modules: (1)the module which transforms numeric to fuzzy values; (2) the inference engine that uses the rules and (3) the module which convert the fuzzy to numeric values. The numeric to fuzzy values transformation is carried out using the fuzzy logic module of MATLAB: Fuzzy Logic Toolbox.
The inference module uses the rules to adjust the parameters. A fuzzy rule is expressed symbolically as: IF <fuzzy proposition> THEN <fuzzy proposition>. Example: âIF <height is low>, THEN <weight is low>â.
To the best of the author's knowledge, there is no methodology in the state-of-the-art for designing inference rules. In most works, the creation of inference rules is reported empiric. Therefore, this work proposes the use of the Universe system, which is based on diffuse compensatory logic, for the generation of inference rules.
In order to validate the adaptive parameters adjustment, a case study has been designed for a decision problem known as Portfolio Project Selection in its bi-objective version. This problem contains imperfect knowledge, due the implicit uncertain of future states of nature that causes imprecision and variability in the information related to the problem, hindering decision making for the decision maker.
In this study case, uncertainty is presented in the available budget, the cost of each project and in the contribution of each project to the objectives and to each given area and region. This work proposes modeling the uncertainty under an interval strategy, which is approached with Grey Mathematics or Interval Mathematics. The problem was tackled by the Grey NSGAII, which is an evolutionary algorithm for solving multi-objective problems, in which two main characteristics are identified:

- The classification by undominated fronts, incorporating elitism in the front 0.
- Incorporation of diversity by calculating crowding distance.

For the generation of inference rules, is necessary to have a training set, to obtain this information,

executions of the Gray NSGA-II algorithm applied to fifteen different instances of the case study were performed. For each instance, we worked with three parameters levels to find behavior patterns. Results were analyzed with the Universe, which is based on compensatory fuzzy logic.
Universe through its rules knowledge discovery module generated a total set of sixty rules, of which twenty nine rules were selected with a truth value above 0.9.
The generated rules were incorporated into the gray NSGAII algorithm, an initial lapse of three executions was established to enter the parameters evaluation, and an improvement of 7% was registered in the number of solutions generated after 300 generations. For the time being, the analysis of the dispersion of the solutions in the best front or found is being made, by means of the Spread metric.

Multi-objective optimization of the supply chain design and operation

Ángel David Téllez Macías[a], **Antonin Ponsich**[a],
Roman A. Mora Gutiérrez[a], **Eric A. Rincón García**[b]

[a]Dpto. de Sistemas, Universidad Autónoma Metropolitana – Azcapotzalco
[b]Dpto. de Ingeniería Eléctrica, Universidad Autónoma Metropolitana – Iztapalapa
Ciudad de México, Mexico
{al2163805867,aspo,mgra,rigaeral}@azc.uam.mx

This work presents a mixed-integer linear (MILP) multi-objective (MO) model for a multi-product supply chain system with 3 echelons (suppliers, manufacture plants, distribution centers and clients). The first objective consists in minimizing the inversion (factories and distribution centers installation) and operation costs (manufacturing and transportation). Besides, the model proposes to simultaneously minimize the total delays on order delivery with respect to an estimated due date. This constitutes a significant improvement of the model introduced in [1], which only considers delays for the last echelon of the supply chain. The resulting MO optimization problem involves determining which factories and distribution centers to be opened, as well as the product quantity to be manufactured in each factory and finally the different product flows among the global system (suppliers $\rightarrow$ plants $\rightarrow$ distribution centers $\rightarrow$ clients). Regarding constraints, upper bound are set over storage capacities in both factories and distribution centers, while the client orders (demand) must be satisfied.
Two solution methods are investigated in this work. The first one is an exact MILP technique, namely the GUROBI solver, using a classical scalarizing function (Augmented Achievement Scalarization Function, AASF) to handle multiple objectives. On the other hand, an adaptation of the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D [2], with the same AASF function) was implemented to solve the problem.
Computational experiments are carried out with both techniques on three randomly generated, small size instances. A normalized Hyper-Volume (HV) indicator is used for result comparison. MOEA/D was executed 10 times for each instance and its parameters were tuned so that both methods have similar CPU times. Table 1 highlights that MOEA/D is not able to perform as good as GUROBI, which obtains the best HV score (1.00) for all instances. However, for larger size instances, the use of a MILP solver will be limited by non-viable CPU times, leaving an open room for future research aiming at improving the performance level of the MO Evolutionary Algorithm.

	Instance 1				Instance 2				Instance 3			
	GUROBI	MOEA/D			GUROBI	MOEA/D			GUROBI	MOEA/D		
		Best	Mean	St.D*		Best	Mean	St.D*		Best	Mean	St.D*
CPU time*	350.0	649.0	670.1	13.88	630	696	708.1	12.49	570	649	679.8	20.77
HV	1.00	0.85	0.59	0.12	1.00	0.90	0.88	0.01	1.00	0.90	0.85	0.03

* *CPU times in seconds, St.D is for Standard Deviation*

Table 1: Comparison GUROBI vs. MOEA/D, both with AASF

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Efficiency of Mexican universities using minimum distance approach in data envelopment analysis

Christian Lizbeth Noguez Moreno [a], Roman Anselmo Mora Gutierrez [a], Eric Alfredo Rincón Garcia [b], Antonin Ponsich [a]

[a]Departamento de Sistemas, Universidad Autónoma Metropolitana - Azcapotzalco
[b]Departamento de Ingeniería Eléctrica, Universidad Autónoma Metropolitana - Iztapalapa

Data Envelopment Analysis (DEA) is a non parametric method that allows to measure the relative efficiency of a set of productive entities. Under this approach, efficiency is the ability of each entity to transform inputs to outputs. In this work, we used DEA to evaluate the efficiency of 60 Mexican universities.
In [3], we found a database with about 211 fields of information for these universities. We divided the fields into 22 inputs and 189 outputs. However, we should not use DEA if the number of universities is lower than the double of the number of inputs multiplied by the number of outputs. Thus, we had to discard some fields. We decided to use a backward principal component analysis to retain 3 inputs and 10 outputs. First we performed a principal component analysis on the correlation matrix of all the 22 inputs variables. Then (22-3) variables had to be discarded. We considered the eigenvector corresponding to the smallest eigenvalue, and rejected the variable with the largest coefficient, in absolute value. Then the next smallest eigenvalue was considered. We repeated this process until only 3 input variables remained. The same strategy was used for the outputs variables. Finally, we included 3 inputs (number of bachelor's degree teachers, number of students in technical education and number of bachelor's degree programs) and 10 outputs (different indexes related to number of papers or documents indexed in ISI web of knowledge, such as number of first author papers in Arts & Humanities Citation Index or number of citations in Science Citation Index journals).
Next, we implemented in GUROBI the additive model of DEA [2]. The optimal solution indicates that 15 universities are efficient under these conditions. Finally, for every non-efficient university we calculated the minimum distance to the efficient frontier using the model proposed in [1]. In this case, the optimal solution shows the areas of opportunity that must be worked to transform a non-efficient university into an efficient entity at the least effort. For example, a university can require more Academic Programs and more Citing to be considered efficient. We want to remark that the set of efficient universities can be seriously modified if we use different input and output variables. Thus, as future research, we want to apply different methods for discarding variables to get a more complete understanding of the strengths and weaknesses of each university.

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Automatic Design of Multiobjective Optimization Evolutionary Algorithm Based on Decomposition

Miriam Pescador-Rojas

ESCOM, Instituto Politécnico Nacional,
Computer Science Department, CINVESTAV-IPN
México City
pescador@computacion.cs.cinvestav.mx

In recent years, there exist a particular interest in the automatic component wise-design of multiobjective evolutionary algorithms, also called AutoMOEAs. This strategy refers to the generation of new algorithms that automatically adapt to the resolution of different classes of multi-objective optimization problems (MOPs). In the literature, we can find benchmark functions that involve instances for continuous or combinatorial optimization problems with characteristics as scalability in the number of objective functions (many-objective optimization), the decision variable space (large scale), complicated Pareto front shapes, as well as, nonseparable or deceptive problems. A big challenge in evolutionary computing is to design algorithms able to adapt to tackle diverse MOPs, this is the case of MOEA/D framework has been able to solve a large amount of these test MOPs varying its algorithmic components as are: the evolutionary operators, selection and replacement mechanisms, scalarizing functions, adaptive weight vectors, neighborhood structures or introducing resource allocation strategies. In this work, we focus on the study of six variants of MOEA/D to employ their components in the generations of new configurations via the use of the offline parameter tool called irace. Our contribution is to derive knowledge about the relationships between the MOEA/D components and the characteristics of MOP classes. Mainly, we examine the scalability in the number of objective functions and the Pareto front shapes.

COLSHADE-Levy for Constrained Optimization

Javier Gurrola-Ramos, **Arturo Hernández-Aguirre**
Oscar Dalmau-Cedeño

Department of Computer Science
Center for Research in Mathematics
Jalisco, 36023 Valenciana, Guanajuato, Guanajuato, México
{francisco.gurrola, artha, dalmau}@cimat.mx

This article describes an extension of the LSHADE [1] algorithm to solve constrained optimization problems: **COLSHADE-Lévy, LSHADE for Constrained Optimization with Levy Flights**. The LSHADE algorithm, (Success Adaptive Differential Evolution with Linearly decreasing Population), is well known for its excellent performance in global optimization. Some bioinspired algorithms that use Lévy flights to explore the search space have reported important experimental results in global optimization. However, Lévy flights have not been used in constrained optimization. COLSHADE-Lévy is one of the very first algorithms to propose the use of Lévy flights in constrained optimization.

COLSHADE-Lévy introduces a new mutation operator based on adaptive Lévy flights, and adopts a constraint handling technique based on Deb's rules[2] . Furthermore, COLSHADE-Lévy wisely combines the DE/current-to-pbest/1/bin mutation used by LSHADE with a proposed mutation DE/levy/1/bin. We describe the cooperation of both mutation operators along the generations. Briefly stated, the DE/levy/1/bin mutation based on Lévy flights excel during the exploration phase whilst the refining solutions phase is performed by the DE/current-to-pbest/1/bin mutation.

The length of the Lévy flights are determined by a Lévy α-stable probability distribution. COLSHADE-Lévy introduces an strategy for adapting the parameters of the Lévy distribution. Therefore, the Lévy flight can vary in length. Short and long flights are randomly generated with larger or smaller probability as successful mutations in the search space bias the parameters of the distribution.

The adopted constraint handling technique is that described by the so called Deb's rules, implemented in a feasibility tournament. Also, an equality constraint is rewritten as an inequality plus a tolerance value (here called ϵ). In our proposal, the ϵ value is dynamic, thus its value is computed from the current generation.

COLSHADE-Lévy has been thoroughly tested using a set of 28 functions of the CEC2017 benchmark [3] used in the competition "real parameter optimization with constraints". In the following tables the best algorithms of the competition at CEC2018 and CEC2017 conference editions are listed. The rank of either algorithm is computed using the same evaluation rules of the competitions, as well as confirmed by running the computer program provided by the competition organizers.

An analysis of COLSHADE-Lévy experimental results, with and without the Lévy flight, clearly shows that the proposed Lévy distribution-based mutation operator explains the success of our proposal.

Algorithm	Competition
A1. CAL-SHADE [4]	CEC2017
A2. LSHADE44+IDE [5]	CEC2017
A3. LSHADE44 [6]	CEC2017
A4. UDE [7]	CEC2017
A5. IUDE [8]	CEC2018
A6. LSHADE44+IEpsilon [9]	CEC2018
A7. ϵMAg-ES [10]	CEC2018
A8. COL-SHADE-Lévy	Our proposal

Table 1: The best algorithms at CEC2017 and CEC2018 competition

	A1	A2	A3	A4	A5	A6	A7	A8
Total rank values	305	231	240	226	129	171	200	147
Final Rank	8	6	7	5	1	3	4	2

Table 2: Computed rank of the algorithms for problems in $D = 10$, based on mean and median values

	A1	A2	A3	A4	A5	A6	A7	A8
Total rank values	294	299	247	284	198	227	222	173
Final Rank	7	8	5	6	2	4	3	1

Table 3: Computed rank of the algorithms for problems in $D = 30$, based on mean and median values

	A1	A2	A3	A4	A5	A6	A7	A8
Total rank values	320	312	255	283	189	245	203	190
Final Rank	8	7	5	6	1	4	3	2

Table 4: Computed rank of the algorithms for problems in $D = 50$, based on mean and median values

	A1	A2	A3	A4	A5	A6	A7	A8
Total rank values	329	284	249	306	219	252	182	195
Final Rank	8	6	4	7	3	5	1	2

Table 5: Computed rank of the algorithms for problems in $D = 100$, based on mean and median values

	A1	A2	A3	A4	A5	A6	A7	A8
Total rank values	1248	1126	991	1099	735	895	807	705
Final Rank	8	7	5	6	2	4	3	1

Table 6: Final rank for all algorithms on all problems and all dimensions

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The Δ_p Newton Method.

Lourdes Uribe[a], **Adriana Lara**[b], **Günter Rudolph**[b], **Oliver Schütze**[d]

[a,b]Escuela Superior de Física y Matemáticas.
Instituto Politécnico Nacional.
Av. Instituto Politécnico Nacional, Edificio 9, Gustavo A. Madero,
Lindavista, 07738 Ciudad de Mexico.
[a]l.uriberichaud@gmail.com, [b]adriana@esfm.ipn.mx

[c]Department of Computer Science
Technical University of Dortmund
Emil-Figge-Straße 50, 44227 Dortmund, Germany
[c]Guenter.Rudolphtu@dortmund.de

[d]Computer Science Department
CINVESTAV-IPN
Av. IPN 2508, C. P. 07360, Col. San Pedro Zacatenco, Mexico City, Mexico
[c]schuetze@cs.cinvestav.mx

Multi-objective Optimization Problems (MOPs) arise in a natural way in diverses knowledge areas. Multi-objective Optimization (MO) aims to get the best advantage (optimize) considering more than one criterion at a time; these criteria are often in conflict with each other. In the current literature there are different methods [DJ14, KL05, DD98] to solve MOPs. Each method seeks to provide a solution in the most satisfactory way possible. It is known that the solution set of this type of problems, the *Pareto set*, typically forms a $(k-1)$-dimensional object, where k is the number of objectives. Therefore, in order to assess the finite approximation of the solution of a MOP obtained by an Multi-objective Evolutionary Algorithm (MOEA), researchers have proposed several performance indicators [SELCC12, ZBT07, VVL98]. Each of these indicators seeks for different properties. This indicators help us select the best approximation between a set of them according to our needs. Δ_p is a performance indicator which simultaneously considers proximity to the theoretical Pareto front and the uniform spread of the computed approximation [SELCC12]. In this work, Δ_p Newton method is introduced as a second-order local search technique which seeks convergence of a whole population of non-dominated individuals toward the best distribution of points according to Δ_p indicator. Results show that under certain conditions a local quadratic convergence rate of this proposed method is expected.

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On the Stability in Dynamic Systems to Analyze Evolutionary Multiobjective Algorithms

Luis A. Quezada-Téllez[a], Saúl Zapotecas-Martínez[a], Oliver Schuetze[b], G. Fernández-Anaya[c]

[a]Departamento de Matemáticas Aplicadas y Sistemas
Universidad Autónoma Metropolitana Cuajimalpa
Av. Vasco de Quiroga 4871, Col. Santa Fe Cuajimalpa, Ciudad de México. C.P. 05348
email: {lquezada,szapotecas}@correo.cua.uam.mx

[b]Departamento de Computación
CINVESTAV-IPN
Av. IPN No. 2508, Col. San Pedro Zacatenco, Ciudad de México. C.P. 07360
email: schuetze@cs.cinvestav.mx

[c]Departamento de Física y Matemáticas
Universidad Iberoamericana
Prolongación Paseo de Reforma 880, Lomas de Santa Fe, Ciudad de México, C.P. 01219
email: guillermo.fernandez@ibero.mx

Through the development of multiobjective evolutionary optimization, the performance assessment of evolutionary algorithms has carried out by using traditional performance indicators (e.g., Hypervolume, IGD, Δ_p indicator, etc.). However, the stability of multiobjective evolutionary algorithms from the dynamic system theory has never been enquired. In this work, we consider the evolutionary algorithms under the aspect of stability as done in dynamical systems. For the case of solutions of differential equations, it is desirable that trajectories are stable under small perturbations in their initial conditions. In this regard, some ideas are outlined to study the stability of multiobjective evolutionary algorithms in the sense of Lyapunov.

On the Deployment of Radio Frequency Identification Readers: A Multiobjective Perspective

Esteban Gamboa García[a], Saúl Zapotecas-Martínez[a], Karen Miranda[b]

[a]Departamento de Matemáticas Aplicadas y Sistemas
Universidad Autónoma Metropolitana Cuajimalpa
Av. Vasco de Quiroga 4871, Col. Santa Fe Cuajimalpa, Ciudad de México. C.P. 05348
email: esteban.gg@outlook.com, szapotecas@correo.cua.uam.mx

[b]Departamento de Sistemas de Información y Comunicación
Universidad Autónoma Metropolitana Lerma
Av. las Garzas 10, El Panteón, Lerma, México. C.P. 05520
email: k.miranda@correo.ler.uam.mx

Radio Frequency Identification (RFID) readers are devices used to obtain information about RFID tags. When the number of RFID tags is high, it is necessary to increase the number of readers capable of reading all tags of a determined area. With the intention of reducing costs, an optimal deployment of RFID readers is required to maximize the coverage in a specific region while minimizing the overlapped area of RFID reader's coverage. In this work, we introduce a multiobjective approach for the optimal deployment of RFID readers. Different scenarios are established simulating big warehouses where these devices are commonly employed. We analyze the performance of traditional multiobjective evolutionary algorithms based on three principles: Pareto dominance, hypervolume indicator, and decomposition.

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NEO 2018 Participants

Name	Institution
Alvarado Iniesta Alejandro	Universidad Autónoma de Ciudad Juárez
Beltrán Fernanda	CINVESTAV-IPN
Bogoya Manuel	Pontificia Universidad Javeriana
Cabo Marta	ITAM
Ceballos Corral Juan	Universidad Autónoma de Baja California
Coello Coello Carlos	CINVESTAV-IPN
Cruz Lara Roides Javier	LANIA
Cruz-Reyes Laura	Instituto Tecnológico de Ciudad Madero
Cuate Oliver	CINVESTAV-IPN
Deb Kalyanmoy	Michigan State University
Dozal Leon	CentroGEO
Estrada-Padilla Alejandro	ITT
Fernández de Bulnes Darian	Instituto Tecnológico de Tijuana
Fernández Jesus	Mutuo Financiera
Gamboa García Esteban	UAM-Cuajimalpa
García-Nájera Abel	UAM-Cuajimalpa
Gomez-Santillan Claudia	Instituto Tecnológico de Ciudad Madero
González Luis Carlos	Universidad Autónoma de Chihuahua
Gurrola-Ramos Javier	CIMAT
Hernández Carlos	Mutuo Financiera
Hernández Cruz Heriberto	CINVESTAV-IPN
Hernández Morales Daniel	Instituto Tecnológico de Tijuana
Juárez Perla	Instituto Tecnológico de Tijuana
Lara Adriana	ESFM-IPN
Laredo David	UC Merced
López Jaimes Antonio	UAM-Cuajimalpa
López López Isaac	CIMAT
López Soto Claudia Orquídea	UNAM
López-López Víctor R	Instituto Tecnológico de Tijuana
Macias-Escobar Teodoro	Instituto Tecnológico de Tijuana
Maldonado Yazmin	Instituto Tecnológico de Tijuana
Martínez Díaz Saúl	Instituto Tecnológico de La Paz
Martínez-Castelán J.N	CIDETEC-IPN
Mezura Montes Efrén	Universidad de Veracruz
Mora Gutiérrez Roman A	UAM-Azcapotzalco
Morales Díaz América Berenice	CINVESTAV-SALTILLO
Morales José Luis	CINVESTAV-IPN
Morales Luna Guillermo	CINVESTAV-IPN

Name	Institution
Muñoz Delgado Luis	Instituto Tecnológico de Tijuana
Noguez Moreno Christian Lizbeth	UAM-Azcapotzalco
Nuñez-Perez J.C.	CITEDI-IPN
Pantoja-García J.S.	CIDETEC-IPN
Pérez Pérez Sergio Luis	Banco de México
Perez-Villafuerte Mercedes	Instituto Tecnológico de Tijuana
Pescador-Rojas Miriam	CINVESTAV-IPN
Ponsich Antonin	UAM-Azcapotzalco
Quezada-Téllez Luis A	UAM-Cuajimalpa
Quiroz Marcela	UV Xalapa
Rangel-Valdez Nelson	Instituto Tecnológico de Ciudad Madero
Rincón García Eric A	UAM-Iztapalapa
Rodríguez Guevara Karla	ESFM-IPN
Rodríguez Sánchez Alberto	UAM-Azcapotzalco
Sandoval Cristian	Universidad Autónoma de Chihuahua
Schütze Oliver	CINVESTAV-IPN
Segura González Carlos	CIMAT
Sun Jian-Qiao	UC Merced
Téllez Macías ángel David	UAM-Azcapotzalco
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Zapotecas-Martínez Saúl	UAM-Cuajimalpa

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