NEO

NUMERICAL AND EVOLUTIONARY OPTIMIZATION

7th International Workshop on
Numerical and Evolutionary Optimization
September 18 - 20, 2019
http://neo.cinvestav.mx

Speakers:

Carlos M. Fonseca, U of Coimbra, Portugal
Laura Cruz Reyes, TecNM, Mexico
Héctor Fraire, TecNM, Mexico
José Martínez Carranza, INAOE, Mexico
Jonatan Peña Ramírez, CICESE, Mexico

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General Chairs:

América Morales, CINVESTAV-IPN
Mario Castelán, CINVESTAV-IPN

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Contents

Additional Information

Foreword

Welcome

Welcome to NEO 2019, the 7th International Workshop on Numerical and Evolutionary Optimization. In this edition, NEO 2019 occurs from September 18 to 20, 2019. Hosting the workshop this year is the Center for Research and Advanced Studies (CINVESTAV), Saltillo Unit, a research institution with more than 50 years making innovation and professional education in science and technology in Mexico. The workshop will take place at the Auditorio Talamás of the Universidad Autonoma de Coahuila, located at the City of Saltillo, Coahuila, 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 2019 edition, there will be participants coming from all over Mexico, as well as from Portugal and China. The NEO 2019 will have more than 40 technical presentations addressing different optimization subjects and dealing with a variety of challenging applications. In particular, the topic of Robotics as a field that clearly benefits from research in numerical optimization, is highlighted. Drones, manipulators, autonomous driving and learning in the fields of computer vision and robotics will be addressed, having an impact in the local community, as Coahuila is one of the leading states in automation for the manufacturing industry.

We hope you enjoy your participation at the NEO 2019. Thank you for your valuable assistance.

Sincerely,

Dr. América Morales, CINVESTAV-Saltillo
Dr. Mario Castelán, CINVESTAV-Saltillo
Dr. Oliver Schütze, CINVESTAV-Mexico

NEO 2019 General Chairs

Acknowledgments

We want to thank all participants that helped to make the NEO 2019 such a great success. In particular, we would like to thank our Keynote Speakers Carlos M. Fonseca (University of Coimbra, Portugal), José Martinez-Carranza (INAOE, Mexico), Héctor Joaquín Fraire-Huacuja (Instituto Tecnológico de Ciudad Madero, Mexico), Laura Cruz Reyes (Instituto Tecnológico de Ciudad Madero, Mexico), and Jonatán Peña Ramírez (CICESE), as well as the Session Chairs for the sessions Robotics: Chidentree Treesatayapun (CINVESTAV-Saltillo), Felipe Machorro (IT Saltillo), Jonatán Peña Ramírez (CICESE); Discrete Optimization: Marcela Quiroz (UV Xalapa); Hybrid Techniques in Optimization: Adriana Lara (IPN) and Lourdes Uribe (IPN); Optimization and Learning in the Energy Sector: Josué Enríquez Zárate (IT Tuxtla Gutiérrez); and Women at NEO (América Morales and Adriana Lara).

Further, we gratefully acknowledge financial support from the Basic Science Group Project No. 285599, from the publisher MDPI, from the Nuclear Power Institute of China (NPIC), from our institution, Cinvestav-IPN, and the Universidad Autonoma de Coahuila 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 2019 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. Also from the students Fernanda Beltran, Lourdes Uribe (IPN) and Oliver Cuate (Cinvestav-IPN).

Finally, 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 2019.

Partners

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Schedule

NEO 2019, Program at a Glance

Timeline	Day 1: September 18	
08:00-09:00	Registration	
09:00-09:15	Opening	
09:15-10:00	*Deep Learning: an Introduction* by Mario Castelán	
10:00-11:00	*An Integrated View of Selection in Evolutionary Algorithms* by Carlos Fonseca	
11:00-11:20	Group photo	
11:20-11:40	Coffee break	Opportunities for studying at Cinvestav
11:40-12:00		
12:00-12:20	Women at NEO **(39,41,25,40)**	Robotics I **(3,28,30,31)**
12:20-12:40		
12:40-13:00		
13:00-13:20		
13:20-14:40	Lunch break	
14:40-15:00	*Network Synchronization of Dynamical Systems: from Static to Dynamic Coupling* by Jonatán Peña	
15:00-15:20		
15:20-15:40		
15:40-16:00	Women at NEO: Round Table	
16:00-16:20		
16:20-16:40	Coffee break	
16:40-17:00	Energy Sector I **(15, 16, 24)**	Stochastic Methods and Chaos **(38,12,34)**
17:00-17:20		
17:20-17:40		

Timeline	Day 2: September 19	
09:00-10:00	*Convolutional Neural Networks for Intelligent Unmanned Aearial Systems* by José Martínez	
10:00-11:00	Tutorial by J. Martinez: *Rapid Algorithm Development for Drones using Gazebo and ROS*	Tutorial by C. Fonseca: *The Attainment Function Approach to Performance Evaluation in Evolutionary Multiobjective Optimization*
11:00-11:20	Coffee break	
11:20-11:40	Tutorial by J. Martinez: *Rapid Algorithm Development for Drones using Gazebo and ROS*	Tutorial by C. Fonseca: *The Attainment Function Approach to Performance Evaluation in Evolutionary Multiobjective Optimization*
11:40-12:00		
12:00-12:20		
12:20-12:40	Coffee break	
12:40-13:00	*A novel multi-objective evolutionary algorithm with fuzzy logic based adaptive selection of operators: FAME* by Héctor Fraire-Huacuja	
13:00-13:20		
13:20-13:40		
13:40-15:00	Lunch break	
15:00-15:20	Hybrid Methods **(5,7,8,22)**	Robotics II **(10, 13)**
15:20-15:40		
15:40-16:00		Energy Sector II **(26,27)**
16:00-16:20		
16:20-16:40	Coffee break	
16:40-17:00	Multi-objective Optimization I **(4,6,9**	Discrete Optimization **(11,20,32)**
17:00-17:20		
17:20-17:40		

20:00-22:00	Gala dinner

Timeline	Day 3: September 20	
09:00-10:00	*New Hybrid Optimization Methods for Bin-packing Problems* by Laura Cruz Reyes	
10:00-11:00	Tutorial by G. Arechavaleta: *Direct Collocation and Geometric Methods for Robot Trajectory Optimization*	Multi-objective Opt. II **(14,21,23)**
11:00-11:20	Coffee break	
11:20-11:40	Tutorial by G. Arechavaleta: *Direct Collocation and Geometric Methods for Robot Trajectory Optimization*	Applications **(33,35,37)**
11:40-12:00		
12:00-12:20		
12:20-12:40	Coffee break	
12:40-13:00	Vision and Navigation **(17,18,19,29)**	
13:00-13:20		
13:20-13:40		
13:40-14:00		
14:00-14:20	Closing session	

Special Sessions

Wednesday Sept., 18

Women at NEO

39 America Morales
Mobile Robotics And Control

41 Dulce Flores-Renteria
Structural Equation Models as a Tool For the Analysis Of Complex Phenomena in the Soil

25 Dania Gutiérrez
Connecting Brains and Robots with Noninvasive Interfaces

40 Adriana Lara
Memetic Algorithms for Multi-Objective Optimization

Robotics I

3 Josue Gómez, America Morales and Chidentree Treesatayapun
Artificial Neural Network Controller Design Based on Pseudo Jacobian Matrix for Robotic System

28 Luis Enrique Hernández Sánchez, Gustavo Arechavaleta Servín and América Berenice Morales Díaz
Establishing Consistent Contact Forces for Multi-Robot Cooperative Task with QP

30 Orlando Reyna-Mireles, Gustavo Arechavaleta and Mario Castelán
Reinforcement Learning for the Lane Following Problem with a Simulated Autonomous Car

31 Jonathan Obregón, Gustavo Arechavaleta and América Morales
Fast Computation of Hierarchical Inverse Dynamics Control

Special Sessions

Wednesday Sept., 18

Energy Sector I

15 Xiaoming Bai, Furui Xiong and Honglei Ai
The Optimization Method for Nuclear Piping System

16 Bihao Wang, Furui Xiong, Qian Huang and Haiyang Song
Optimal Design of DVA for Vibration Reduction of Piping System

24 María De Los Ángeles Gómez López and Josué Enríquez Zárate
Aerodynamic and Modal Analysis of Wind Turbine Blade Caused by the Effect of Erosion

Stochastic Methods and Chaos

38 Dulce Martinez-Peon, Roberto Lara-Villanueva, Marco Ivan Ramirez Sosa Morán, Laura Gomez-Sanchez, Angela Benavides-Rios and Francisco Gerardo Benavides-Bravo
Characterization of Motor Imagery Paradigm for Wrist and Forearm Using an Algorithm Based on the Hurst Exponent

12 Jesús-Adolfo Mejía-de-Dios and Efrén Mezura-Montes
Pseudo-Feasible Solutions: a Warning Sign for Evolutionary Computation in Bilevel Optimization

34 Reynaldo Domínguez-Castillo and Nicandro Cruz-Ramirez
Gibbs Sampling as Sampling-Based Method in Imbalanced Learning

Special Sessions

Thursday Sept., 19

Hybrid Methods

5 Oliver Cuate, Lourdes Uribe, Adriana Lara, Oliver Schuetze, Antonin Ponsich and Saul Zapotecas
A New Hybrid Evolutionary Algorithm for the Treatment of Equality Constrained Mops

7 Lourdes Uribe, Günter Rudolph, Adriana Lara and Oliver Schuetze
$\Delta_{p}-$ Newton Method for Unconstrained Optimization

8 Lourdes Uribe, Adriana Lara, Kalyanmoy Deb and Oliver Schuetze
A Novel Gradient Free Local Search Operator for Constrained Multi-objective Optimization

22 Oliver Schuetze
Multi-objective Evolutionary Algorithms from the Mathematical Programming Point of View

Robotics II

10 Luis Gerardo De La Fraga
Robot Arm Motion Planning with a Multi-Objective Algorithm

13 Jesús Savage, Stalin Muñoz, Marco Negrete and Carlos Rivera
Robotics State Machine Behaviors Derived with Genetic Algorithms

Special Sessions

Thursday Sept., 19

Energy Sector II

26 Javier Carmona, Leonardo Trujillo and Josué Zárate
Machine Learning, Fault Detection in Wind Turbine Blades And Related Databases: a Review of the State-of-the-Art

27 Josué Enríquez-Zárate, Perla Juarez-Smit, Javier Carmona and Salvador de Lara
Modeling of the Dynamic Response in a Gas Turbine Using Experimental Vibrations with Machine Learning

Multi-objective Optimization I

4 Oliver Cuate and Oliver Schütze
Pareto Explorer for finding the Knee for Many Objective Optimization Problems

6 Oliver Cuate, Lourdes Uribe, Adriana Lara and Oliver Schuetze
A Benchmark for Equality Constrained Multi-objective Optimization

9 María Fernanda Beltrán Llorente and Oliver Schütze
The Pareto Tracer for General Inequality Contraints

Discrete Optimization

11 José Manuel Muñoz Contreras, Daniel Eduardo Hernández Morales, José Juan Tapia Armenta and Leonardo Trujillo
Implementation of Genetic Programming with Geometric Semantic Operators in GPU

20 Blanca Cecilia López-Ramírez and Nareli Cruz Cortés
A Multi-Objective Design for Finding High Nonlinearity S-boxes

32 David Martínez-Galicia, Efrén Mezura-Montes and Alejandro Guerra-Hernández
Analysis of Differential Evolution variants for parameter tuning of Decision Trees inductive algorithms

Special Sessions

Friday Sept., 20

Multi-objective Optimization II

Applications

Special Sessions

Friday Sept., 20

Vision and Navigation

II

Invited Speakers

Carlos M. Fonseca

An Integrated View of Selection in Evolutionary Algorithms

University of Coimbra, Portugal

Talk Abstract

Selection plays a double role in evolutionary algorithms. The selection of solutions from the current solution set (or population) to produce new candidate (offspring) solutions through variation is known as parental selection, whereas the selection of solutions to discard in order to make room for new solutions in the population is usually called environmental selection. Intimately related to selection is the concept of solution fitness, which is typically related to the objective function(s) of the problem at hand. In practice, both types of selection must be implemented, although different evolutionary algorithms often emphasize either one or the other. In particular, it is common for only one type of selection to depend on fitness. Selection also has the double purpose of steering the search towards more promising regions of the search space by favouring the best solutions available (exploitation) while maintaining a sufficient level of diversity in order to be able to escape local optima and/or find multiple good solutions (exploration). Over the years, many different approaches to selection in evolutionary algorithms have been proposed in the literature, with the balance between exploration and exploitation gaining heightened importance in the context of multiobjective optimization. However, parental and environmental selection have continued to be seen as different operators, and to be implemented separately. In this talk, selection methods and fitness assignment strategies are reviewed and discussed from the unifying perspective of portfolio optimization, where the fitness of a solution is interpreted as an investment in that solution, and solution diversity emerges naturally from the need to balance return and risk in the portfolio. In addition, parental and environmental selection can be seamlessly integrated in the portfolio optimization formulation. Application examples illustrate the main aspects of the approach.

Short Biography

Carlos M. Fonseca is an Associate Professor at the Department of Informatics Engineering of the University of Coimbra, Portugal, and a member of the Evolutionary and Complex

Systems (ECOS) group of the Centre for Informatics and Systems of the University of Coimbra (CISUC). He graduated in Electronic and Telecommunications Engineering from the University of Aveiro, Portugal, in 1991, and obtained a Ph.D. in Automatic Control and Systems Engineering from the University of Sheffield, U.K., in 1996. His research has been devoted mainly to evolutionary computation and multi-objective optimization, with a focus on computationally efficient approaches to preference articulation and experimental performance evaluation in evolutionary multi-objective optimization. He is the Scientific Representative of the Grant Holder of COST Action CA15140 – Improving Applicability of Nature-Inspired Optimisation by Joining Theory and Practice (ImAppNIO), and the leader of a Working Group on Software in that Action. He has served as General, Technical or Track co-Chair of several major international conferences on evolutionary computation, and is a member of the Evolutionary Multi-Criterion Optimization and of the Parallel Problem Solving from Nature Steering Committees.

José Martínez-Carranza

Convolutional Neural Networks for Intelligent Unmanned Aerial Systems

Instituto Nacional de Astrofísica, Óptica y Eletrónica (INAOE)

Talk Abstract

Unmanned Aerial Systems (UAS) have become an essential tool in several civilian and industrial applications. However, there still exist a strong dependency on a pilot for the UAS to be operated and deployed. Applications such as inspection, exploration or monitoring require the execution of several flight mission that may turn tedious and tiresome to the operator, prone to human failure with catastrophic results. In recent years, Artificial Intelligent (AI) has been leveraged by the revival of Neural Networks (NN), but in particular, by a type of NN that exploits parallel computing implementations on Graphics Processing Units (GPUs), namely the Convolutional Neural Networks, whose implementation through several layers have given rise to what is known now as Deep Learning (DL). With impressive results in domains where the combinatorial factor exploded, DL has shed light by enabling the development of solutions that can even run in real time. Thus, the field of autonomous UAS, this is without operator, has not been an exception to the use of DL, especially for the development of methods that enable a UAS to take autonomous intelligent decisions. In this talk, a number of examples involving DL and intelligent UAS will be presented. In this spirit, It will be discussed how current state of the art challenges can be better tackled with the DL-based technology. The talk will conclude with some remarks and forecasts on how DL will also leverage the future of the next generation of intelligent UAS.

Short Biography

ose Martinez-Carranza is Associate Professor in the Computer Science Department at the Instituto Nacional de Astrofísica, Óptica y Eletrónica (INAOE). He obtained a BSc in Computer Science (Cum Laude) from the Benemérita Universidad Autónoma de Puebla in 2004, and an MSc in Computer Science (Best Student) from INAOE in 2007, both institutions in México. In 2012, he received his PhD from the University of Bristol in the UK, where he also worked as Postdoctoral Researcher from 2012 to 2014. He received the highly prestigious Newton Advanced Fellowship (2015-2018), granted by the Royal Society in the UK to work with autonomous drones in GPS-denied environments. He also leads a Mexican team that has achieved outstanding performance in International Drone Competitions: 1st Place in the IROS 2017 Autonomous Drone Racing competition; 2nd Place in the International Micro Air Vehicle competition (IMAV) 2016 and ranked 4th in the IMAV 2017. His team is the first Mexican team to win an International Autonomous Drone Competition.

Héctor Joaquín Fraire-Huacuja

A Novel Multi-objective Evolutionary Algorithm with Fuzzy Logic Based Adaptive Selection of Operators: FAME

Instituto Tecnológico de Ciudad Madero, Mexico

Talk Abstract

We propose a new method for multi-objective optimization, called Fuzzy Adaptive Multi-objective Evolutionary algorithm (FAME). It makes use of a smart operator controller that dynamically chooses the most promising variation operator to apply in the different stages of the search. This choice is guided by a fuzzy logic engine, according to the contributions of the different operators in the past. FAME also includes a novel effective density estimator with polynomial complexity, called Spatial Spread Deviation (SSD). Our proposal follows a steady-state selection scheme and includes an external archive implementing SSD to identify the candidate solutions to be removed when it becomes full. To assess the performance of our proposal, we compare FAME with a number of state of the art algorithms (MOEA/D-DE, SMEA, SMPSOhv, SMS-EMOA, and BORG) on a set of difficult problems. The results show that FAME achieves the best overall performance.

Short Biography

Héctor Joaquín Fraire Huacuja is a research professor in the postgraduate courses in Computing at the Tecnológico Nacional de México Campus Cd. Madero. He holds a Bachelor's Degree in Mathematics and a Master's Degree in Information Systems from the Universidad Autónoma de Nuevo León and a PhD in Computer Science from the Centro Nacional de Investigación y Desarrollo Tecnológico del Tecnológico Nacional de México. He has been recognized for 13 consecutive years as a member of the Sistema Nacional de Investigadores of CONACYT, in which he currently has Level II. His research is focused on the exact and heuristic optimization of complex problems with practical applications in science and engineering. He has published more than 30 articles in indexed journals (JCR), 65 book chapters, and 12 articles in non-indexed journals. He has been a principal researcher in 5 research projects and has directed 6 doctoral theses.

Laura Cruz Reyes

New Hybrid Optimization Methods for Bin-packing Problems

Instituto Tecnológico de Ciudad Madero, Mexico

Talk Abstract

Cloud computing is a new scenario that is taking a lot of importance to improve the traditional management of organizations, and of society in general. In this context, a key aspect is to find planning strategies that allow efficient use of resources. Among these strategies is the placement of resources in the cloud that can be modeled as a problem of accommodating objects. Other real scenarios can also be modeled in this way, hence the importance of the classic problem of accommodating objects in containers called BPP (Bin Packing Problem). This problem belongs to the NP-hard class, so it is considered unsolvable in polynomial time. For problems of this kind, the search for efficient algorithms is an area in constant evolution. In this talk, the most outstanding hybrid approaches of the state of the art for the BPP solution will be presented, emphasizing the optimization methods based on evolutionary grouping and virtual savant. The last one is a new paradigm based on machine learning to automatically generate parallel solvers that have learned how to solve a problem.

Short Biography

Laura Cruz-Reyes received the Ph.D. degree in Computer Science from the National Center for Research and Technological Development, México, in 2004. She is a full-time Professor of Computer Science at Madero Institute of Technology of National Mexican Institute of Technology, since 1984. In addition, she is serving as head of the research group on Intelligent Optimization since 2006. She belongs to the Mexican National System of Researchers with level II. Her research interests are in intelligent optimization techniques, algorithmics, autonomous agents, evolutionary computation, machine learning, multicriteria decision, and logistics.

Jonatán Peña Ramírez

Network Synchronization of Dynamical Systems: from Static to Dynamic Couplings

CICESE, Mexico

Talk Abstract

A complex system is defined as a set or union of two or more subsystems, interconnected with each other, whose dynamic behavior is, in general, different from the individual behavior of each subsystem. Examples of complex systems are: collective behavior (human and animal), engineering systems (eg cars, aircraft), social networks (eg Facebook, Twitter), to name just a few. From the point of view of Dynamic Systems theory, a complex system can be seen as a network of systems that interact with each other through a medium, called coupling, and whose interconnection, called

network topology, can be fixed or variant in time. In general, each subsystem in the network is modeled by a set of nonlinear ordinary differential equations and the coupling between the subsystems is considered static. It is in this context that the present talk proposes to analyze complex systems from a Dynamics and Control approach which allows understanding the dynamic and structural properties of complex systems that interact either through dynamic couplings or through flexible couplings, discover new phenomena and behaviors in these systems (e.g. eg pattern formation, chaotic behavior, chimera states, bifurcation scenarios, among others), and eventually seek its application in the development of control algorithms that induce cooperative and / or coordinated behavior in physical systems, e.g. ex. robotic systems.

Short Biography

Jonatán Peña Ramírez was born in Tulancingo de Bravo, Hidalgo, Mexico. He is an specialist in the field of analysis and control of nonlinear systems. In February 2013, Jonatán received his PhD degree in Mechanical Engineering from Eindhoven University of Technology, in The Netherlands, working on synchronization of coupled dynamical systems under the supervision of Prof. Dr. Henk Nijmeijer. In April 2013, he was invited by the Japan Science and Technology Agency (JST) to join, as a postdoctoral researcher, to the project: “The Mathematical Theory for Modelling Complex Systems and Its Transdisciplinary Applications in Science and Technology” at the University of Tokyo, Japan. Currently, he is a postdoctoral researcher at CICESE (Center for Scientific Research and Higher Education at Ensenada) working in the project: “Synchronization of dynamical systems: analysis, synthesis, and applications”. Jonatán is member of the National System of Researchers (SNI-I). His research interests are in the areas of control and synchronization of dynamical systems, perturbation theory, mathematical modelling, network synchronization, and chaotic systems.

III Special Sessions

Robotics

Chairs: Dr. Chidentree Treesatayapun, Dr. Felipe Machorro, Dr. Jonatán Peña



Nowadays robots are available in common activities as medical scanning devices, prosthesis, cars with some degree of autonomy, at home as cleaning robots and also as toys. To understand what a robot is we take the international federation of robotics definition: a robot is an actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks. That is, a robot can manipulate and transport objects but can also assist humans to rehabilitate different limbs and even to replace them, e.g. in surgery or as automated wheelchair. To accomplish these tasks several techniques have been developed to define their movements and to achieve the required degree of autonomy. In that direction optimization plays an important role to obtain reliable paths that allow robots fulfill their tasks in an efficient and safe way.

Topics:

- Mobile robotics: wheels, drones, mobile manipulators, aquatic robots.
- Service robots.
- Robots for medical applications.
- Robots in agricultural applications.
- Techniques to design robots.
- Control and planning algorithms.
- Cooperative robots: manipulators, multivehicle systems indoors and outdoors.

Discrete Optimization

Chair: Dr. 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.

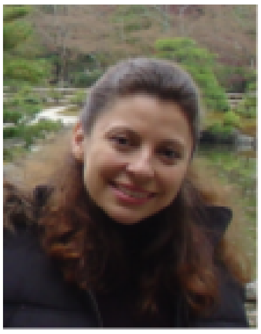
Topics

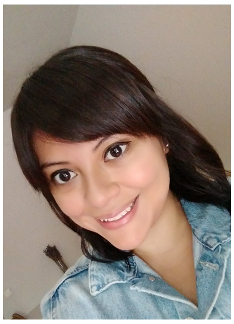
- Single and multi-objective optimization.
- Deterministic approaches.
- Approximation algorithms.
- Randomized algorithms.
- Heuristics.
- Meta-heuristics.
- Simulation.
- Stochastic programming.
- Real-world applications.

Hybrid Techniques

Chairs:

- **Dr. Adriana Lara**
- **M.Sc. Lourdes Uribe**





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 from all over the world to present and discuss recent advances in set oriented numerical methods in particular in the context of optimization. Methods of this kind iterate (or evolve) entire sets instead of considering point-wise iterative methods and are thus in particular advantageous if a thorough investigation of the entire domain is required and/or the solution set is not given by a singleton.

Topics

- Memetic Algorithms.
- Hyperheuristics.
- Hybrid Metaheuristics.
- Coupling heuristic/stochastic techniques with exact methods.
- Scalarization-based MOEAs.
- Two-phase algorithms.

Optimization in the Energy Sector

Chair: Dr. Josué Enríquez Zárate

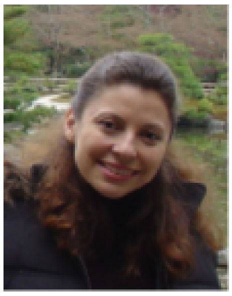
One of the most important technological challenges we face today is the development of efficient and sustainable energy resources, the environmental and financial impact of how we address this challenge will affect our society as a whole. Like all other engineering challenges, optimization, efficient tuning and predictive analysis will all play a role in this challenge. The goal of this special session is to begin an important discussion between those working on developing new Energy related applications and technology an those the growing NEO community, so that the problems faced by the former can be posed, and hopefully, solved with the techniques being developed by the latter.

Topics

- Optimization of Energy Resources.
- Optimization of Energy Systems.
- Applications of Machine Learning in Energy problems.
- Position papers on the importance of Optimization and Learning in this area

Women at NEO

Chairs:
- **Dr. América Morales**
- **Dr. Adriana Lara**

Nowadays our society relies on drinking water, electricity, horticulture mass production, vaccines, and transportation and even with commodities as air-conditioned or heat systems, which are the result of the scientific research and product development. Despite this, there are only a reduced number of people doing research, accordingly to the 2017 World-Bank report from a population of 7.5 billions, only a 0.093% are working in research, which includes scientific and research assistants (UNESCO report in Science, technology ad innovation, 2017). From this 0.093% only the 28% are women, i.e., 1.96 millions from a total of 7.5 billions or a 0.026% from total world population (UNESCO: Women in Science, 2017).

With the data above described is not surprising to encounter women under-representation in the scientific research and development all over the world. Women are known for their capacity as problem solvers, this is an excellent incentive to attract them in areas as engineering, mathematics and physics, which typically have been dominated by men (BBC News: The engineering gap, 2016).

A way to increase the number of women in science, in particular in optimization and robotics areas, is to provide gatherings where the presence of female researchers is highlighted. With this idea in mind Women at NEO 2019 presents talks that involve their research field and how they impact. Additionally, this space will be an opportunity to discuss what been a woman and a scientist mean.

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

IV Contributed Talks

List of Talks

September 18

- América Morales.*Mobile Robotics And Control*
- Dulce Flores-Rentería. *Structural Equation Models as a Tool For the Analysis Of Complex Phenomena in the Soil*
- Dania Gutiérrez.*Connecting Brains and Robots with Noninvasive Interfaces*
- Adriana Lara. *Memetic Algorithms for Multi-Objective Optimization*
- Josué Gómez, América Morales and Chidentree Treesatayapun.*Artificial Neural Network Controller Design Based on Pseudo Jacobian Matrix for Robotic System*
- Luis Enrique Hernández Sánchez, Gustavo Arechavaleta Servín and América Berenice Morales Díaz. *Establishing Consistent Contact Forces for Multi-Robot Cooperative Task with QP*
- Orlando Reyna-Mireles, Gustavo Arechavaleta and Mario Castelán. *Reinforcement Learning for the Lane Following Problem with a Simulated Autonomous Car*
- Jonathan Obregón, Gustavo Arechavaleta and América Morales.*Fast Computation of Hierarchical Inverse Dynamics Control*
- Xiaoming Bai, Furui Xiong and Honglei Ai.*The Optimization Method for Nuclear Piping System*
- Bihao Wang, Furui Xiong, Qian Huang and Haiyang Song.*Optimal Design of DVA for Vibration Reduction of Piping System*
- María De Los Ángeles Gómez López and Josué Enríquez Zárate .*Aerodynamic and Modal Analysis of Wind Turbine Blade Caused by the Effect of Erosion*
- Dulce Martínez-Peon, Roberto Lara-Villanueva, Marco Iván Ramírez Sosa Morán, Laura Gómez-Sánchez, Ángela Benavides-Ríos and Francisco Gerardo Benavides-Bravo. *Characterization of Motor Imagery Paradigm for Wrist and Forearm Using an Algorithm Based on the Hurst Exponent .*
- Jesús-Adolfo Mejía-de-Dios and Efrén Mezura-Montes.*Pseudo-Feasible Solutions: a Warning Sign for Evolutionary Computation in Bilevel Optimization*
- Reynaldo Domínguez-Castillo and Nicandro Cruz-Ramírez.*Gibbs Sampling as Sampling-Based Method in Imbalanced Learning*

September 19

- Oliver Cuate, Lourdes Uribe, Adriana Lara, Oliver Schuetze, Antonin Ponsich and Saul Zapotecas.*A New Hybrid Evolutionary Algorithm for the Treatment of Equality Constrained Mops*
- Lourdes Uribe, Günter Rudolph, Adriana Lara and Oliver Schuetze.Δ_p- *Newton Method for Unconstrained Optimization*
- Lourdes Uribe, Adriana Lara, Kalyanmoy Deb and Oliver Schuetze.*A Novel Gradient Free Local Search Operator for Constrained Multi-objective Optimization*
- Oliver Schuetze.*Multi-objective Evolutionary Algorithms from the Mathematical Programming Point of View*
- Luis Gerardo De La Fraga.*Robot Arm Motion Planning with a Multi-Objective Algorithm*
- Jesús Savage, Stalin Muñoz, Marco Negrete and Carlos Rivera.*Robotics State Machine Behaviors Derived with Genetic Algorithms*
- Javier Carmona, Leonardo Trujillo and Josué Zárate.*Machine Learning, Fault Detection in Wind Turbine Blades and Related Databases: a Review of the State-of-the-Art*
- Josué Enríquez-Zárate, Perla Juárez-Smit, Javier Carmona and Salvador de Lara.*Modeling of the Dynamic Response in a Gas Turbine Using Experimental Vibrations with Machine Learning*
- Oliver Cuate and Oliver Schütze.*Pareto Explorer for finding the Knee for Many Objective Optimization Problems*
- Oliver Cuate, Lourdes Uribe, Adriana Lara and Oliver Schuetze.*A Benchmark for Equality Constrained Multi-objective Optimization*
- María Fernanda Beltrán Llorente and Oliver Schütze.*The Pareto Tracer for General Inequality Constraint*
- José Manuel Muñoz Contreras, Daniel Eduardo Herández Morales, José Juan Tapia Armenta and Leonardo Trujillo.*Implementation of Genetic Programming with Geometric Semantic Operators in GPU*
- Blanca Cecilia López-Ramírez and Nareli Cruz Cortés.*A Multi-Objective Design for Finding High Nonlinearity S-boxes*
- David Martínez-Galicia, Efrén Mezura-Montes and Alejandro Guerra-Hernández.*Analysis of Differential Evolution variants for parameter tuning of Decision Trees inductive algorithms*

September 20

- Teodoro Macías-Escobar, Laura Cruz-Reyes and Bernabé Dorronsoro.*Application of Multiple Preference Incorporation Approaches to Solve Dynamic Multi-Objective Optimization Problem*
- Luis Torres-Treviño and Luis Márquez-Vega.*Multi-objective Optimization of a Flock of Robots for Location Tasks*
- José Manuel Ortiz-Salazar, Saúl Zapotecas-Martínez and Abel García-Nájera.*Multi-Objective Optimization using Decomposition: The Case of the Whale Optimization Algorithm*
- Andrea Padilla, Diana Gamboa Loaiza, Paul J. Campos, José R. Cárdenas-Valdez and Carlos E. Vázquez-López.*Nonlinear Analysis for a Type-1 Diabetes Model Focus on T and Beta Cells Behavior*
- José Cárdenas, Everardo Inzunza-González, Manuel De J. García-Ortega, Andrés Calvillo Téllez and J. C. Núnez-Pérez.*Hardware Implementation of the Phase Distortion to Amplitude Conversion Algorithm Applied for a 1.84-Ghz PA*
- Juan Gabriel Ruiz and Oliver Schüetze.*The Design of Graphical User Interfaces through Automatic Optimization Methods: A Review of the State of the Art*
- Luis Gerardo De La Fraga, Sergio Albeto Herrera Castro and Ernesto Olguín Díaz.*Visual-Inertial Odometer with a Marker*
- Luis Gerardo De La Fraga and Michel Torres Alonso.*Augmented Interaction with a Deformable Object*
- Pablo Arturo Martínez.*Camera-Radar Data Fusion for Traffic Participants Detection in Intelligent Intersection System*
- Carlos Acuna, Mario Castelán and Gustavo Arechavaleta .*A New Probabilistic Segmentation Method of Lanes for Autonomous Vehicles*

Mobile Robotics and control

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Abstract
In the present work some results are provided in the research lines of mobile robot formation, autonomous driving, coordination strategies with fusion of sensors for the use of mobile manipulators in manufacturing processes, and in the application of modeling tools, control and vision to achieve production systems in greenhouses. Also a brief in the author's experience as a research woman in an engineering field is also presented.

Structural equation models as a tool for the analysis of complex phenomena in the soil

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Abstract

Structural equation models (SEM) can be defined as the use of two or more structural equations (cause-effect) to model multivariate relationships and allows the construction of a graphic representation of a complex network of relations. SEMs are a statistical methodology that takes a confirmatory approach (e.g. hypothesis test) in the analysis of a structural theory of some phenomenon. Typically, this theory represents “causal” processes that generate observations in multiple variables. The term structural equation model conveys two important aspects of the procedure: a) that the causal process under study is represented by a series of structural equations (e.g. regressions), and b) that these structural relationships can be graphically modeled to facilitate a clear conceptualization of the theory under study. The use of these models has been increasing in ecological studies, as they provide a multidimensional reference framework necessary to capture the complexity of ecological relationships and networks. However, its use to explain the soil carbon exchange is still restricted. The understanding of the mechanistic relations between the factors that regulate the soil carbon exchange will potentially allow us to promote the maintenance of soil carbon stores, strategy necessary to achieve the greenhouse gas emissions objectives proposed by the Intergovernmental Panel of Climate Change (IPCC). The SEM are a promising tool to support the investigation of soil ecology, in particular the soil carbon exchange, thus, the models can be considered as a methodological referent on the belowground interactions.

Key words: structural equation models; soil respiration; multivariant relationships.

Connecting brains and robots with noninvasive interfaces

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As part of the "Women at NEO" session, I will be talking about the work that the laboratory of Biomedical Signal Processing at Cinvestav Monterrey has been developing in the area of brain-computer interfaces (BCI). Our work is currently focused in studying functional brain connectivity through noninvasive BCI, and this work has the potential of providing a better understanding about how the brain works, as well as in the development of new rehabilitation techniques. Furthermore, our laboratory has been a committed supporter of women in science, and this has had an impact in the number of graduates from the lab: five out of six graduated PhD students are women that now play important roles in academia and industry.

Memetic Algorithms for Multi-objective Optimization[a]

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In this talk, we briefly describe the philosophy behind the design of memetic algorithms. We focus on the benefits of combining specific (local) processes with Evolutionary Algorithms, in particular, to deal with Multi-objective Optimization Problems.

Free model control of robot manipulator end-effector tracking by an equivalent system using an adaptive Kalman filter

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Abstract: This paper proposes a free-model task space control for a robot's end-effector. The robot is considered a non-linear discrete time system, using the data driven control and model free control approach. An adaptive Kalman filter provides an equivalent system by means of the robotic Jacobian matrix, which only needs the input-output data to control the robot's position. Besides, we design the adaptive gains for sliding mode controller, using a neuro-fuzzy network structure. In the simulation was tested the performance of the equivalent Jacobian matrix and, slidng mode controller with adaptive gains for tracking control. We also provided a Lyapunov analysis of the equivalent model to guarantee convergence based on the adaptive Kalman filter.

Keywords: robot's end-effector, equivalent system, adaptive Kalman filter, adaptive gains, sliding mode control

1. INTRODUCTION

The methods of nonlinear system control intend to solve the main problematic for control design as: nonlinearities, parametric uncertainties, and superposition properties losses. The robot's motion control is a common issue for nonlinear control. Furthermore, the robotic application field has matured, and the robots manipulator control design needs to enhance the task execution accuracy. The classic control techniques allow to deal with main robot tasks, but the inaccuracy in the mathematical model can cause low performance in the robot. In contrast, currently the use of free model control has gained attention, in parallel with the current research tendency to use data control. The Data Driven Control (DDC) allows working with an equivalent system by the dynamic linearization model, Hou and Jin (2011). The Model Free Adaptive Control (MFAC) based on DDC has been implemented in robotic systems: Zen et al. (2018) designed an equivalent system by the pseudo Jacobian matrix, and Li et al. (2018) applied the Jacobian estimate by an adpative Kalman filter to control a continumm robot. In previous work was presented a robot free model task space control with a proportional controller, Gómez et al. (2018). The objective of this paper is to test the end-effector tracking control with an equivalent system provided by an adaptive Kalman filter. The robotic plant is an omnidirectional mobile manipulator; whit 5 dof in the robotic arm and 3 dof in the omnidirectional mobile platform. The Strong Tracking Kalman Filter (STKF) is a class of adaptive algorithm which allows to obtain the Jacobian matrix as an equivalent model, regarding the robot input-output data. The main characteristics of the equivalent model provided by the STKF are: the robustness against uncertainties, and instantaneous change detection.

As well, we designed the controller based on the equivalent system and in the model free control approach. The control proposal is a Sliding Mode Controller (SMC) with on-line adaptive gains tuning; the Fuzzy Rules Emulated Network structure (FREN) adapts the controller gains, in the work presented by Treesatayapun and Uatrongjit (2005). The basic principles of SMC allow to an equivalent system deals with nonlinearities, external disturbance and uncertainties. Aditional, FREN adapts the SMC gains in terms of control error change. The simulation results show the equivalent model control performance, and we introduce the system model stability analysis. The structure of this paper is: section 2 describes of the unknown nonlinear discrete time system, section 3 presents the simulation results, and section 4 gives the conclusions.

2. DISCRETE TIME SYSTEM

The position of the robot's end-effector $\chi(k) = f(q_n)$ is:

$$\chi(k) = [p(q)] \ \in \mathbb{R}^m \subset SE(3), \tag{1}$$

where $p(q)$ denotes the end-effector position; m is the robot dof and n is the end-effector dof. The end-effector velocity approximates within a discrete time derivative:

$$\frac{\chi(k+1)-\chi(k)}{Ts} = J_A(k)\left[\frac{q(k)-q(k-1)}{Ts}\right] \ \in \mathbb{R}^m, \tag{2}$$

⋆ CONACyT support acknowledgment.

where the Jacobian matrix is $J_A(k) = \dfrac{\partial f(\chi(k+1))}{\partial f(q_n(k))} \in \mathbb{R}^{m\times n}$ nad Ts is the sampling time

$$\frac{\chi(k+1)-\chi(k)}{Ts} = J_A(k)\omega(k) \in \mathbb{R}^m, \tag{3}$$

and $\omega(k) \in \mathbb{R}^n$ represents the discrete joint velocities

2.1 Equivalent model system

The Jacobian vector $J_v(k)$ contains the dynamics system from the Jacobian matrix $J_A(k)$ in the next way

$$J_v(k) = \left[\frac{\partial f_x}{\partial q_n}\ \frac{\partial f_y}{\partial q_n}\ \frac{\partial f_z}{\partial q_n}\right]^T \in \mathbb{R}^a, \tag{4}$$

where x, y and z are the end-effector axes, and $a = mn$ is the multiplication of the Jacobian matrix subspaces m and n. The measurement matrix $H(k)$ is a diagonal matrix with the control signals $\omega(k)$:

$$H(k) = \begin{bmatrix} [\omega_1(k)\ \dots\ \omega_n(k)] & & 0 \\ & \ddots & \\ 0 & & [\omega_1(k)\ \dots\ \omega_n(k)] \end{bmatrix} \in \mathbb{R}^{m\times a} \tag{5}$$

The Strong Tracking Kalman Filter (STKF) is an adaptive algorithm with estimation error tracking, Li et al. (2018). Thus, fading factor λ_k enhances the robustness against uncertainties, and the updated covariance matrix Q_k captures the instantaneous change of the Jacobian. The STKF estimates the Jacobian vector $J_v(k)$ in equation (6)

$$\begin{aligned} K_F(k) =& P(k)H^T(k)\left[H(k)P(k)H^T(k)\right]^{-1} \\ P(k+1) =& \left[I - K(k)H(k)P(k)\right]\lambda_k + Q_k \\ \hat{J}_v(k+1) =& \hat{J}_v(k) + K(k)\left[\frac{\Delta\chi}{Ts} - H(k)\hat{J}_v(k)\right], \end{aligned} \tag{6}$$

where $K_F(k) \in \mathbb{R}^{a\times n}$ is the Kalman gain, $P(k+1) \in \mathbb{R}^{a\times a}$ is the error covariance matrix, $\hat{J}_v(k+1) \in \mathbb{R}^a$ is the updated state of Jacobian vector. The next expression defines the error estimation

$$v_n(k) = \frac{\Delta\chi}{Ts} - H(k)\hat{J}_v(k) \in \mathbb{R}^m, \tag{7}$$

the updated covariance matrix Q_k is

$$Q_k = K_F(k)\hat{C}(k)K_F(k), \tag{8}$$

the matrix $\hat{C}(k)$ is the results of weighting quadratic error estimation

$$\hat{C}(k) = \frac{1}{N}\sum_{n=k-N+1}^{k} v_n v_n^T, \tag{9}$$

the value of b_k restricts the value of λ_k in the equation (10)

$$\lambda_k = \begin{cases} b_k, & \text{when } b_k \geq 1 \\ 1, & \text{when } b_k < 1 \end{cases} \tag{10}$$

the value of b_k is in terms of the trace value of matrices M_k and N_k

$$b_k = \frac{tr\,[N_k]}{tr\,[M_k]}, \tag{11}$$

M_k and N_k compute in equation (12)

$$\begin{aligned} N_k &= V_k - H(k)Q_kH(k)^T \\ M_k &= H(k)P(k)H(k)^T, \end{aligned} \tag{12}$$

the matrix V_k is

$$V_k = \begin{cases} v_0v_0^T & k = 0 \\ \frac{0.95V_{k-1}+v_kv_k^T}{1.95} & k \geq 1 \end{cases} \tag{13}$$

2.2 System stability analysis

This section presents the stabilty analysis of the equivalent system $\hat{J}_v(k+1)$ provided by the STKF, according by the next assumptions:

Assumption 1: The output is observable: $H(k)\hat{J}_v(k) = \dfrac{\Delta\chi}{Ts}$, $\forall k > 0$.

Assumption 2: The initialization of the Jacobian vector $J_v(0) \in \mathbb{R}^a$, and covariance matrix are in a normal distribution $P(0) \in \mathbb{R}^{a\times a} \sim N(J_{v_0}, P_0)$.

Assumption 3: The covariance matrix $P(k)$ is a positive definite matrix $\in \mathbb{R}^{a\times a}$, $P^{-1}(0) > 0$.

By the estimation error in the equation (7) the cost function proposed

$$\xi(k) = \frac{1}{2}v_n(k)v_n^T(k), \tag{14}$$

at each time step updates the value of the $\hat{J}_v(k+1)$

$$\hat{J}_v(k+1) = \hat{J}_v(k) - K_F(k)\frac{\partial\xi}{\partial\hat{J}_v}, \tag{15}$$

the chain rule method calculates the term $\dfrac{\partial\xi}{\partial\hat{J}_v}$ by

$$\frac{\partial\xi}{\partial\hat{J}_v} = \frac{\partial\xi}{\partial v_n}\,\frac{\partial v_n}{\partial H\hat{J}_v}\,\frac{\partial H\hat{J}_v}{\partial\hat{J}_v} = v_n(k)\left[-1\right]H(k), \tag{16}$$

the equation (6) has determined the updated vector $\hat{J}_v(k+1)$ and considering the next Lyapunov's function

$$V(k+1) = \frac{1}{2} v_n(k+1) v_n^T(k+1), \tag{17}$$

the change in the Lyapunov's function is

$$\Delta V(k+1) = V(k+1) - V(k), \tag{18}$$

the change in the error estimation is

$$\Delta v_n(k+1) = v_n(k+1) - v_n(k), \tag{19}$$

the equation (18) now is

$$\Delta V(k+1) = \Delta v_n(k) \left[v_n(k) + \frac{1}{2} \Delta v_n(k) \right], \tag{20}$$

$\Delta v_n(k)$ approximates in the next way

$$\Delta v_n(k) \approx \frac{\partial v_n}{\partial \hat{J}_v} \Delta \hat{J}_v, \tag{21}$$

where

$$\frac{\partial v_n}{\partial \hat{J}_v} = \frac{\partial v_n}{\partial H \hat{J}_v} \frac{\partial H \hat{J}_v}{\partial \hat{J}_v} = -H(k), \tag{22}$$

the equation (21) and equation (22) produces

$$\Delta v_n(k) \approx \frac{\partial v_n}{\partial \hat{J}_v} \Delta \hat{J} = -H(k) K_F(k) v_n(k), \tag{23}$$

the change in the Lyapunov's function is

$$\Delta V(k) = -H(k) K_F(k) v_n^2(k) \left[1 - \frac{1}{2} H(k) K_F(k) \right], \tag{24}$$

according with the stability condition $\Delta V < 0$

$$0 < K_F(k) < 2H^{-1}(k), \tag{25}$$

the Kalman filter gain $K_F(k)$ should lie in the range indicated in equation (25) to guarantee system stability.

2.3 Controller design

This section introduces the SMC with adaptive gains, and the control error defines

$$e(k) = \chi(k) - \chi_d(k) \in \mathbb{R}^m, \tag{26}$$

and the sliding mode surface is

$$s(k) = \Delta e(k) + G(k) e(k) \in \mathbb{R}^m, \tag{27}$$

$G(k) \in \mathbb{R}^{m \times m}$ is a diagonal matrix that contains the adaptive gains for SMC: $G_x(k), G_y(k)$, and $G_z(k)$

the equation (28) uses a continuous smooth function for SMC

$$\nu(k) = -\tanh\left(\frac{s(k)}{\epsilon} \right) \in \mathbb{R}^m, \tag{28}$$

where $\epsilon > 0$, it is possible to calculate the signals of the controller using the pseudoinverse of $\hat{J}_A(k)$

$$\omega(k) = \hat{J}_A^+(k) \nu(k) \in \mathbb{R}^n, \tag{29}$$

and the updated joint position

$$q(k+1) = q(k) + \omega(k) \cdot Ts \in \mathbb{R}^n \tag{30}$$

The Fuzzy Rules Emulated Network (FREN) adapts the gains matrix $G(k)$. The architecture of artificial network has 4 distinct layers in terms of: (1) input error $e(k)$; (2) linguistic variables $\mu_i(k)$; (3) linear consequence parameters β_i; and (4) adaptive gains $G(k)$. The Fig. 1 shows the architecture of Fuzzy Rules Emulated Network Adaptive Gains (FRENAG), and the output gives the adaptive gains as:

$$G(k) = \sum_{i=1} \beta_i \mu_i(k) \tag{31}$$

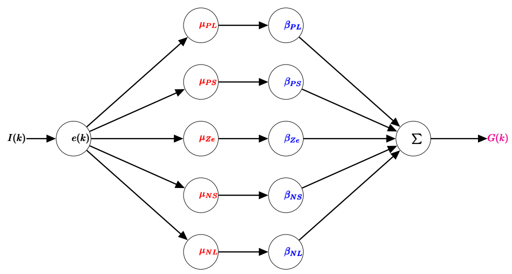

Fig. 1. Fuzzy rules emulad network architecture for adaptive gains.

The membership functions designs for adaptive gains are in the Fig. 3 and the linear consequence parameters are in table 1. Where the linguistic variables: PL is positive large, PS

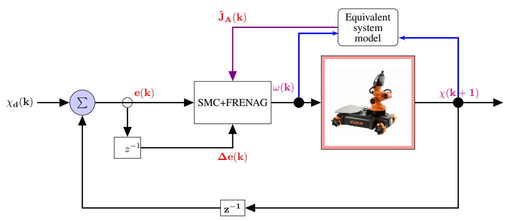

Fig. 2. Control block diagram of an equivalent system control.

is positive small, Ze is zero, NS is negative small, and NL is negative large. The membership functions μ_i are designed in terms of the end-effector axes, and the linear consequence parameters βi (constant values) are tuned intuitively.

3. SIMULATION RESULTS

3.1 Robotic system

The base of study is the Kuka youBot mobile manipulator, which has 3 dof for omnidirectional mobile platform and 5 dof for manipulator arm ($n = 8$). The joint configuration space is the cartesian product $ES(2) \times \mathbb{T}^5$. The kinematic model of Kuka youBot generates the input and output data for simulations, but it is not included in the robot controller. The Fig. 2 shows the diagram of the robot and controller approach.

3.2 Tracking control

The robot home position is $\chi(0) = [0.1430, 0, 0.6480, 0, 0, 0]$, and the desired trajectory is a circle giving for the next functions:

$$\begin{aligned} \chi_{xd}(k) =& 0.5\sin(\frac{4\pi k}{kmax}) \\ \chi_{yd}(k) =& 0.5\cos(\frac{4\pi k}{kmax}) \\ \chi_{zd}(k) =& 0.55 \end{aligned} \tag{32}$$

The end-effector follows a circle with x and y and z remains in constant position, in the equation (32) $kmax$ is the maximum time index of the simulation. The Fig. 4 shows the simulation results of end-effector tracking trajectory, the function tracking for the end-effector axes, the convergence of the control errors, the gains adaptiation, and the joint velocity as a control signal (mobile platform and robot arm), while the equivalent Jacobian system complete the control. The equivalent Jacobian system fulfills the demand of the end-effector trajectory control by the proposed controller based on SMC and FRENAG.

4. CONCLUSION

We found that an equivalent system based on data driven control (STKF) can control the end-effector trajectory without any requirement of the mathematical model. As well, we demonstrated the stability analysis of the Jacobion matrix estimation (equivalent system) by the STKF, and we proposed the adaptive gains for a SMC based on neuro-fuzzy artificial network architecture (FREN). The control advanteges of the equivalent system $\hat{J}_v(k)$ are: free model control, on-line data driven controller, input-output data requirements, and model independeny. The simulations for tracking control tested the performance of the Jacobian matrix estimation and control. An equivalent system based on Jacobian estimation by STKF has been tested in the end-effector tracking control. The control is based on the principles of model free adaptive control; the robot control only requires the input-output data system. The use of FREN lets an on-line adaptive gains tuninig for the SMC, which captures the changes and uncertienties in the robotic system. The simulation test the end-effector tracking control. Moreover, the theoretical analysis of the STKF was demonstrated using Lyapunov stability analysis. As a future plan we will extend the work to cover: the proposed controller stability analysis and the robot's orientation control.

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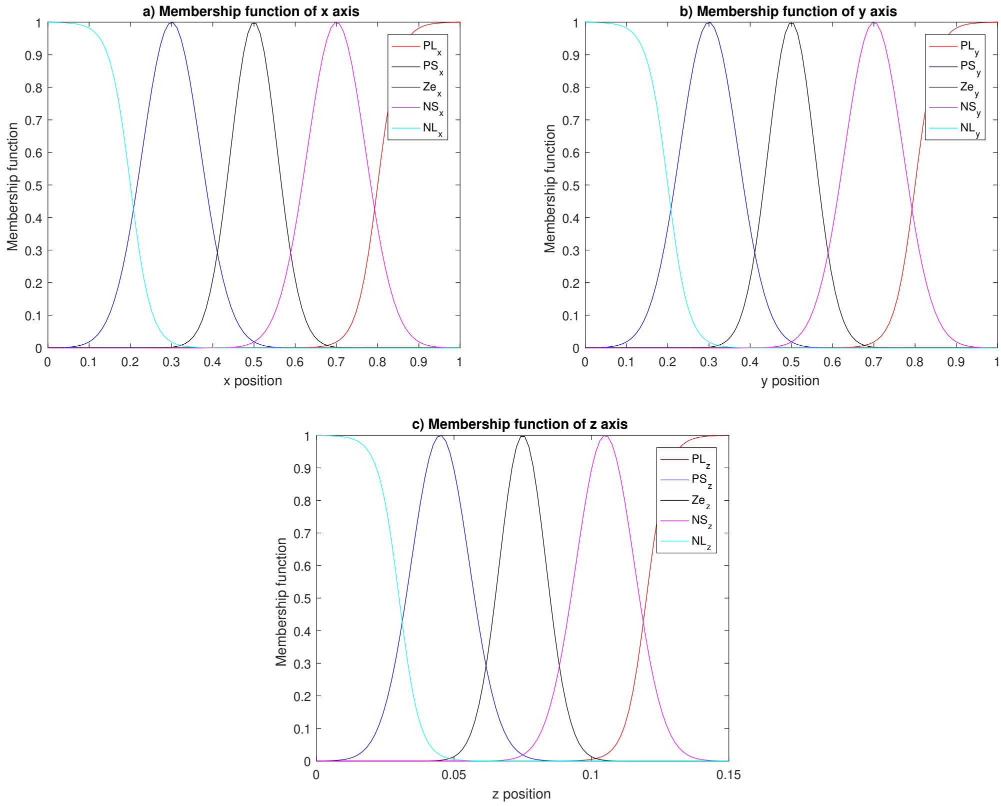

Fig. 3. Membership function for the end-effector tracking $\chi(k) = [x,\ y,\ z]$: a) membership functions of x axis, b) membership functions of y axis, and c) membership functions of z axis.

Table 1. Linear consequence parameters of adaptive gains parameters for $G_x(k)$, $G_y(k)$ and $G_z(k)$.

Name	Parameters	$G_x(k)$ values	$G_y(k)$ values	$G_z(k)$ values
Positive Large	β_{PL}	1	1.25	0.25
Positive Small	β_{NL}	0.85	1	0.35
Zero	β_{Ze}	0.85	0.5	0.75
Negative Small	β_{NS}	0.25	0.5	0.85
Negative Large	β_{NL}	0.15	0.25	1

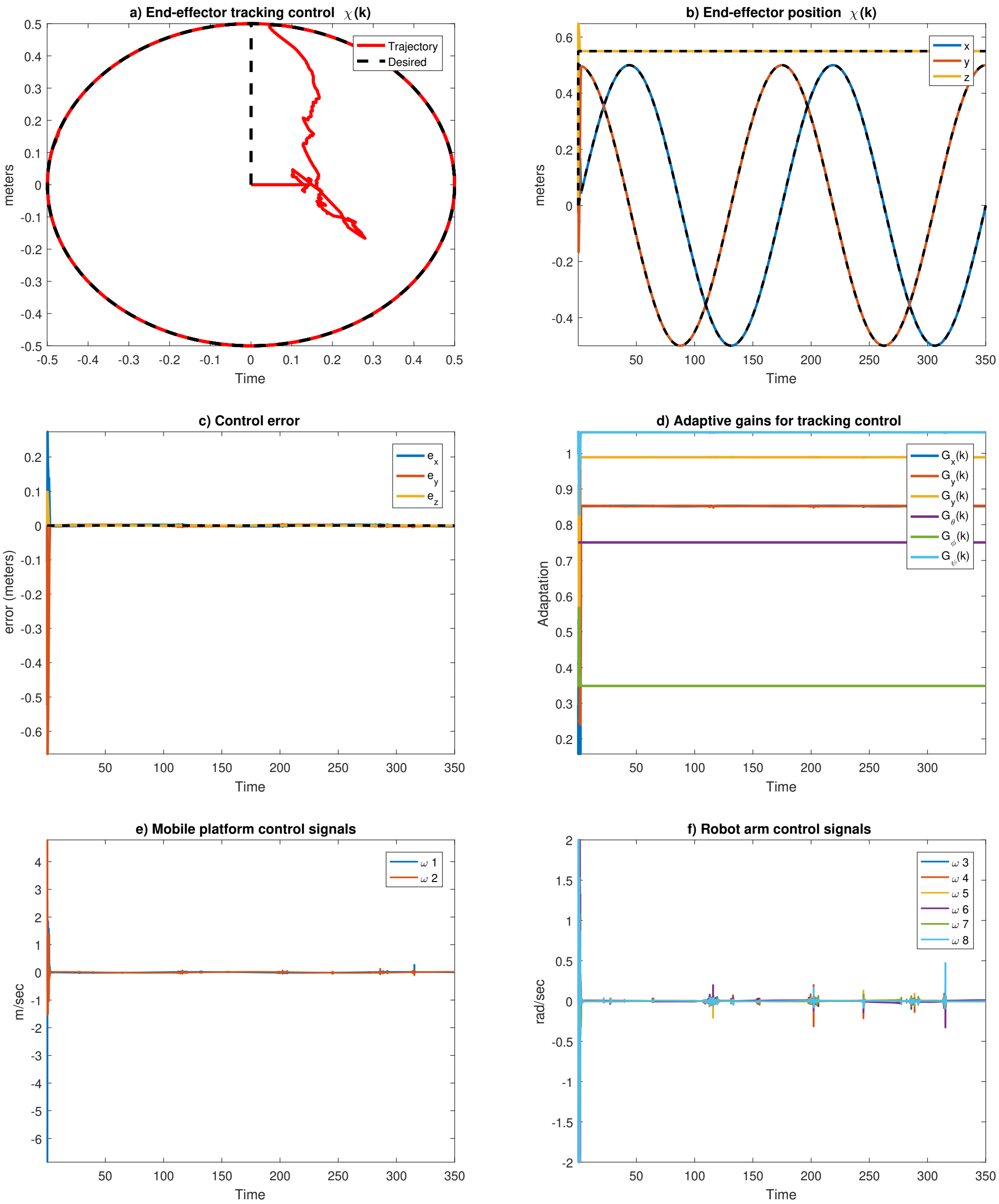

Fig. 4. Performance of end-effector tracking control: a) end-effector desired trajectory (cricle), b) end-effector desired functions, c) end-effector tracking error, d) mobile platform control signals, and e) robot arm control signals.

Establishing consistent contact forces for multi-robot cooperative task with QP

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To achieve multiple tasks at the same time when robots work in a cooperative way (i.e., object transportation), optimization represents an efficient alternative to fulfill these tasks. In this work we propose an optimal solution using a unique quadratic program (QP) which encompasses the entire multi-robot system, including the dynamic model of robots and objects as rigid bodies, and the contact forces that interact between them as linear constraints. The proposed method provides efficiency and physical consistency necessary to establish motion tasks directly on the sub- actuated objects through contact forces. The approach is tested with 2 identical mobile planar robots of 4 (d.o.f.). Dynamic simulations are performed to illustrate the control in task space through QP, which minimizes a decision variable that contains the optimal joint accelerations, joint torques and contact forces. The results obtained show how the positional errors of both the robots and the object converge asymptotically.

Reinforcement learning for the lane following problem with a simulated autonomous car

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Robotics and Advanced Manufacturing
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Reinforcement learning methods can be used to enable an agent to learn optimal behaviours in order to maximise a reward signal. A key component of this framework is the design of the function that gives such signal. However, the formulation of appropriate reward functions depends largely on the problem. In this paper we propose a reward function useful to solve a simplified version of the lane following problem with the Dubins car, i.e., a nonholonomic car where only the steering is actuated. The agent is successfully trained to take the most rewarding actions given its current state based on artificial neural networks. We show some results with value-based and policy gradient methods. In particular, the main results of the proposed strategy were obtained with an asynchronous advantage actor-critic algorithm.

Fast computation of hierarchical inverse dynamics control

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Control based on hierarchical inverse dynamics is a common scheme to exploit the redundancy of robots, which allows them to simultaneously execute non-conflicting tasks. This scheme relies on the generalized inversion of task-Jacobians with a weighting matrix that ensures dynamic consistency, and on the computation of null-space projectors. Conventional algorithms that performs such computations become as expensive as many tasks are included in the hierarchy, mainly because of the Jacobian weighted inversions. In this work, we present a reformulation of the hierarchical inverse dynamics scheme using QR factorization and Cholesky decomposition. As a result, the hierarchical inverse dynamics solutions reduce to the inversion of only triangular matrices, without the need of computing null-space projectors, and fulfilling dynamic consistency.

The optimization method for nuclear piping system

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1 ABSTRACT

The piping system in the nuclear power plant is extremely complex. The traditional trial method for the optimization is time-consuming and experience-dependent. Moreover, it rarely obtains the layout with best mechanical property using the trial method. In order to improve the traditional method, an automatic optimization method is proposed in present work. The genetic algorithm is employed during the mechanical analysis of piping system. In this method, both the piping layout and the piping support can be optimized concurrently. Moreover, based on the optimization method, a piping optimization theory assistant tool (POTATO) is developed. Some optimization instances in the nuclear power plant is shown in this paper. Comparing with the layout from the trial method, the one from present automatic method have more mechanical margin. The stress ratios at all the conditions are less than the limitation. Meanwhile, the time cost in present method is less than the trial method. Thus, present method is more efficient than the traditional method, and is significant for the piping layout in nuclear engineering.

2 Introduction

The piping system in the nuclear power plant (NPP) is extremely complex, and the design and qualification is a challenged problem. Conventionally, an initial design of the piping system is usually proposed based on the engineers' experience. Then, the mechanical analysis is performed to ensure the structural integrality of piping system. Mechanical analysis aims at examine the capability of piping system that can withstand various loads include thermal, seismic, deadweight, etc. If the initial design fails to satisfy the mechanical requirement, the piping system would be modified and the mechanical analysis is redone in association.

Obviously, such trail-and-error process with manual design tuning would be extremely time-consuming and experience-dependent. Moreover, manual tuning can seldom guarantee optimal designs in any sense. Therefore, the investigation of automatic optimization procedures for the nuclear piping system design is of very strong significance, especially for new reactor design that largely differs from its predecessors. To obtain the best piping layout case, researchers proposed some optimization method base on the heuristic optimization method. Chiba proposed an optimization method for the support arrangement of piping system (Chiba, 1996). Collina proposed a method to optimize the position and stiffness of supports in the piping system (Collina, 2005). In Mahinthakumar’s work, the seismic response is supposed to be the target function, and the support is optimized based on the genetic algorithm (Mahinthakumar, 2005). To simplify the optimization problem in these analyses, the authors usually set the target function as the maximum stress or maximum reacted force. Meanwhile, the optimization process in these work are based on some specific in-house code, and no general software can be found in these publications. However, during the nuclear piping design, several load case and the combination of each load case should be considered according the relevant design code (e.g. ASME, RCC-M). Thus, the optimization target is more complex that the one used in previous publications. In this work, the genetic algorithm (GA) is employed for the optimization of piping system design by the Nuclear Power Institute of China (NPIC). Under the framework of parametric optimization, both the piping layout and the piping support can be fine tuned concurrently. Additionally, an in-house optimization code named Piping Optimization Theory Assistant Tool (POTATO) is developed and applied to the design of piping system of several NPPs.

3 Scope of mechanical analysis of piping system

The mechanical analysis of piping system in a nuclear power plant under examine normally includes stress and fatigue analysis. The purpose of mechanical analysis is to ensure the following items are satisfied as per various industrial code that are practiced in nuclear engineering (ASME, RCC-M, etc.)

- Structural Integrity
- Operational Integrity
- Optimal Design

To meet these objectives, several load cases are considered for analysis. Besides design & normal operating conditions, typical transient conditions are also included in the analysis for service levels A to D as required by the ASME code. Typical static transient load conditions occurred in pressurized water reactor include, but are not limited to, the following:

- Internal and external pressures;
- Deadweight of important component and its assemblies combine with flow effect (added mass, added stiffness, etc.);
- Net effect results from deadweight, thermal expansion, inner pressure and dynamic loads at pipe supports or connecting points. These loads are computed from a larger system-level dynamical analysis model and are applied as force boundaries of pipe supports and connecting points computation domain;
- Earthquakes and vibrations, if any;
- Temperature effects, either constant or transient.

4 Formulation of optimization problem in the NPP

In the nuclear piping design process, choosing proper deployment of pipe support is the main concern for optimization. Tunable variable of support design includes the support location and the support type. These variables influence the overall distribution of stress of the entire piping system. In this study, these two types of variables are considered are input parameters.

From the output side, the mechanical requirements of piping system include stress criteria and functionality assurance. These requirements can be easily quantified according to the design code. The stress requirements are related to the safety of piping system under operational/accident load case. The functionality requirements are related to the valve function under seismic conditions.

The multi-objective optimization problem is reduced to a bi-objective problem herein with two general categories of output to minimize.

4.1 Input variable

In the optimization problem, the input variables are set as

- Support location;
- Segment length of pipe;
- Elbow radius;
- Type of supports;

4.2 Constraints

Constraints of present optimization problem are defined as follows,

- Stress ratios at Level A/B;
- Stress ratios at Level D;
- Functionality requirements;
- Geometrical limitation,
- Stress limitation;
- Reaction force limitation;

Note that these constrains are computed via the linear/nonlinear combinations of state variables under each design.

4.3 Objectives

Two categorizes of optimization objectives are the maximum value of the stress ratios and the maximum value of the valve acceleration under dynamical load case.

5 Software developments

An automatic optimization software piping optimization theory assistant tool (POTATO) is developed based on the method proposed in section 2. The genetic algorithm is implemented in the software MATLAB, and the piping stress analysis is using the software PIPESTRESS. The interface of the POTATO is shown in Fig.1. It can be observed that this software includes 7 modules. The functions of these modules are:

Pre-process module:

The pre-process module is used to convert the original PIPESTRESS input files to the Bas file (a special format defined in POTATO with the extension ".bas"). The Bas file is an extension of PIPESTRESS input file, some keywords and grammars related to the optimization parameters and boundary conditions are defined in the Bas file.

Bas file selection module:

The optimization parameters and their boundary conditions can be defined in the "Bas file selection module". A well-defined "Bas file" can be selected as the input file of POTATO software.

Boundary/Spatial constraint module:

These two modules are used to define the boundary constraints and spatial constraints, respectively.

Algorithm selection module:

In the "algorithm selection" module, different optimization algorithm can be selected, and default algorithm is genetic algorithm.

Run module:

The "run" module is used to start and visualize the process of the optimization.

Result module:

After the optimization is done, the summary of all the possible piping layout case can be visualized in a table via the "result" module.

Fig. 1 The interface of the POTATO

6 Instances and discussions

6.1 Instance #1

A piping system is shown in Fig.2. They are made of austenitic stainless steel, Type Z2CN1810. The outside diameter is 24.5mm. The design condition for the piping system is 100℃ and 2.5MPa. Considering the constriction from building, the optimization range is marked in Fig.2. The supports #A~#E can be moved in the zone with dash line, respectively. The pipe #1 can be moved horizontally in the potential zone. The support index and corresponding optimization rang are shown in Table 3. Two optimization cases are used in present work. In case 1, only the position of the supports is optimized. In case 2, the position and function of the support can be optimized concurrently.

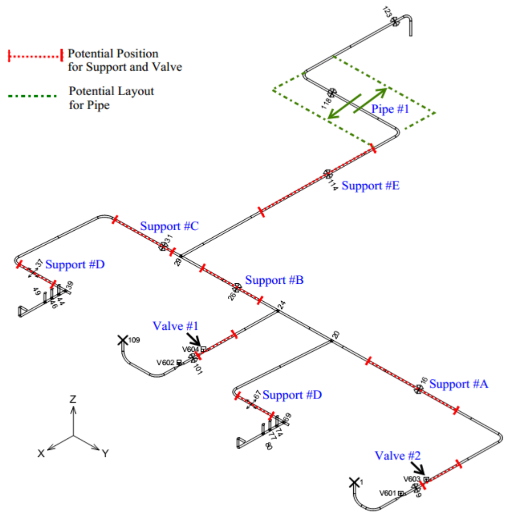


Fig. 2 The Scheme Diagram of pipes and supports

Table 2 The Support Index and Corresponding Length Range

Characteristic coordinate	Support Index				
	#A	#B	#C	#D	#E
Lower boundary (mm)	105	20	30	30	2010
Upper boundary (mm)	185	80	110	90	3030

The comparison of stress ratio for different layout case is shown in Table 3. It can be observed that the maximum stress ratio in optimized case is much lower than that in original case. Moreover, the optimized case 2 have a better result than the case 1.

Table 3 Stress ratios in different layout case

	Level 0	Level A		Level B	Level D	Max.
Original case	0.666	0.374	0.31	0.231	0.483	0.666
Optimized case 1	0.469	0.361	0.319	0.572	0.589	0.589
Optimized case 2	0.374	0.091	0.191	0.416	0.314	0.416

6.2 Instance #2

An expansion loop on the steam generator of HPR1000 for measurement is shown in the Fig.3. The stress ratio of the original piping layout is shown in Table 4. It can be observed that all the stress ratio is exceed the limitation of design code. For instance, the stress ratio of TFM052MN at level A criteria is 6.508, which exceed the limitation over 500%. To optimize the expansion loop, several length parameters marked as A~L is defined as the optimized value (shown in Fig 3). The software POTATO proposed in present work is used to optimize the expansion loop piping layout. Then result of optimized piping layout can be found in the Table 5. It can be observed that all the stress ratios are below the limitation. An example of the comparison between the original layout and optimized layout is shown in the Fig.4. It can be seen that most of the length defined in Fig. 3 is modified, and consequently the layout of the piping changed dramatically.

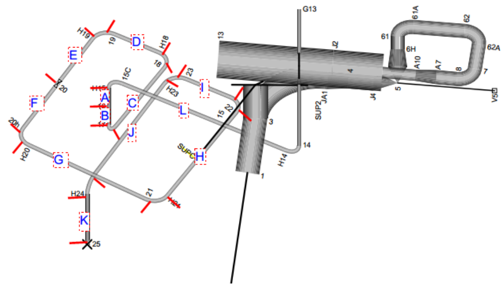


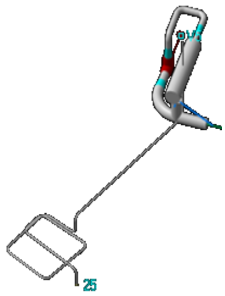
Fig. 3 The schematic of the expansion loop and its optimized location.

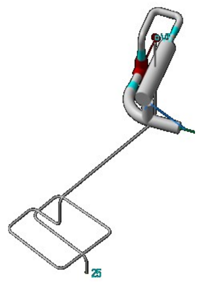
Table 4 The stress ratio of the original piping layout

Piping	Level 0	Level A	Level B	Level D
TFM010MN	0.366	3.125	1.462	2.588
TFM020MN	0.219	2.642	0.718	0.975
TFM030MN	0.384	1.525	1.216	1.488
TFM052MN	0.427	6.508	1.264	1.867
TFM053MN	0.372	1.253	2.293	2.496
TFM054MN	0.361	0.825	1.293	1.279
TFM055MN	0.368	1.71	0.877	1.016
TFM056MN	0.227	3.516	2.718	3.082
TFM057MN	0.224	1.015	0.746	1.083
TFM058MN	0.338	1.785	0.74	1.098
TFM059MN	0.235	2.602	3.169	3.842
TFM060MN	0.243	1.497	0.794	1.011
TFM061MN	0.247	1.83	0.646	0.947
TFM062MN	0.434	2.113	0.815	1.052
TFM063MN	0.219	0.945	0.815	2.113

Table 5 The stress ratio of the optimized piping layout

Piping	Level 0	Level A	Level B	Level D
TFM010MN	0.328	0.929	0.745	0.916
TFM020MN	0.296	0.988	0.955	0.991
TFM030MN	0.264	0.992	0.785	0.981
TFM052MN	0.340	0.980	0.844	0.923
TFM053MN	0.316	0.809	0.716	0.844
TFM054MN	0.324	0.813	0.779	0.870
TFM055MN	0.281	0.997	0.669	0.791
TFM056MN	0.278	0.977	0.793	0.981
TFM057MN	0.264	0.996	0.771	0.972
TFM058MN	0.360	0.905	0.671	0.811
TFM059MN	0.493	0.854	0.859	0.989
TFM060MN	0.371	0.792	0.703	0.784
TFM061MN	0.335	0.890	0.681	0.810
TFM062MN	0.348	0.858	0.778	0.880
TFM063MN	0.301	0.797	0.620	0.919





a) Original layout **b) Optimized layout**

Fig. 4 The comparison between the original and optimized nuclear piping

6.3 4.3 Discussions

Two instances of piping layout optimization using POTATO are introduced in this section. In the instance #1, the support location and the support function are optimized to enlarge the safety margin of the nuclear piping. In the instance #2, the stress ratio greatly exceeds the limitation. Due to the limitation of space, no additional support can be placed on the expansion loop. Then the piping is described by some critical length for optimization. Benefit from the software POTATO, all the stress ratio in 15 piping are optimized and reduced dramatically in a very short time.

In the traditional trial method for the optimization, it takes days of time for engineers to optimized one piping layout in instances #2. Usually they need to try hundreds layout case to find out one satisfied the design code, namely the stress ratios under all criteria are below the limitation. However, the application of the software POTATO reduced the time for optimization from days to hours. The engineers only need to define the optimization parameter, and run the software. Thousands of layout case can be generated according to genetic algorithm automatically. Then the optimized layout case will be proposed after the algorithm is converged. Comparing with the traditional trial method, present method can improve the process of nuclear piping design and analysis effectively.

7 CONCLUSIONS

In present work, an automatic optimization method for nuclear piping layout and mechanical analysis is proposed. The genetic algorithm is employed as the optimization method, the support location, support function and pipeline layout can be optimized concurrently. Moreover, the software called piping optimization theory assistant tool (POTATO) is developed. Comparing with the trial method, the automatic method can give more mechanical margin. Meanwhile, the time cost in the automatic method is less than the trial method. Thus, present work is significant for the piping layout in nuclear engineering.

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Optimal design of DVA for vibration reduction of piping system

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The piping system is widely used in the nuclear power plant, and is one of the main paths of vibration transmission in Reactor Coolant System (RCS). Since the vibration is generally periodical, the dynamic vibration absorber (DVA) is known for its capability on reducing pipe vibration. Here, a type of DVA that combines translational-type DVA and a rotational-type DVA is proposed for isolation of piping system vibration under harmonic excitation. First of all, the piping system is modeled with beam elements and the multi-DOF DVA is modeled with translational and rotational mass-spring elements. In this model, kinematic equations of the vibration absorber and the nonuniform beam are coupled. Then, design of experiments (DOEs) is carried out with Latin Hypercube Sampling (LHS). The surrogate model is constructed based on the DOE points. Kriging interpolation is applied for the data-driven model. The optimization problem is solved via Efficient Global Optimization (EGO) algorithm which updates the surrogate model by sampling new points at each iteration. The optimization variables include the location of vibrations absorbers and stiffness parameters. Optimizations are carried out to fine tune the deployment strategy with maximum vibration reduction at several locations.

AERODYNAMIC AND MODAL ANALYSIS OF WIND TURBINE BLADE CAUSED BY THE EFFECT OF EROSION

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Abstract

This paper presents a numerical study of wind turbine blade of 1 kW of power concerned to the damage in his surface around of cut through section and tip end. The effect of erosion can be caused in several areas and layers of a wind turbine blade, and reduce the dynamic performance and useful life of structure. In this work the analysis is applied in the leading edge on the both sides (up/down) evaluating the slipstream effect due to the mechanical unbalance caused by the material loss, inducing a variation in the power coefficient of the wind turbine, which can reduce the maximum power extraction from wind turbine. The unbalance can induce a vibration problem due to the fluctuation in the natural frequency of the wind turbine blade, which is associated to the magnitude of mass removed due to the material loss. The aerodynamic issue is studied with open source Qblade software and load calculations is reviewed using Blade Element Momentum (BEM) theory. Similarly, structural problem is conducted with modal analysis using a Finite Element Model (FEM) software. Finally, numerical analysis are presented to show the performance of wind turbine blade from relationship between mechanical damage and the aerodynamic response considering a percentage of erosion around of 18%.

Characterization of Motor Imagery paradigm for wrist and forearm using an algorithm based on the Hurst Exponent

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Content
Kinesthetic Motor Imagery (KMI) is the imagined forces that the subject uses to move a limb without muscle tension, [1, 2]. KMI has been probed as a robust paradigm that can be part of the rehabilitation or training session to gain strength, [3]. In the present work electroencephalogram (EEG) signals were recorded from 5 healthy subjects that executed KMI of the wrist and forearm, three degrees of freedom: flexion/extension, pronation/supination and abduction/adduction. The raw EEG signals are preprocessed using a Whitening and Independent Component Analysis (ICA) to map the raw signals into electrodes space. An algorithm based on semivariogram and the Hurst exponent was used for the characterization of the three different KMI tasks, [4]. The results showed that the characterization using the Hurst Exponent allows a high level of persistence higher than 90%. This result can be used to steer an external agent like exoskeletons that required multiple commands.

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Pseudo-Feasible Solutions: A Warning Sign for Evolutionary Computation in Bilevel Optimization

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Evolutionary Computation is useful to solve complex real-world problems in single-level optimization. However, to obtain good accuracy a high computational cost is needed particularly when a hierarchical optimization structure is introduced. This work details some challenges for evolutionary algorithms adapted for bilevel optimization. Some important definitions and results are reported in order to identify the main issues when population-based algorithms are required to solve this emergent optimization process. Pseudo-feasible values are defined and characterized to expose the possible unfair comparison of solutions carried out in some test problems.

Gibbs Sampling as Sampling-Based method in Imbalanced Learning

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Supervised Learning is one of the most studied areas of Artificial Intelligence. So far, the best results often use a class-balanced dataset for the training process. However, there exist many problems where it is not possible to have this kind of data; thus, these problems have to be analyzed from the unbalanced perspective. The easiest way to deal with such a situation is by generating artificial data so that classes can be balanced. Despite this solution, most of these imbalanced-learning methods look for maximizing classification accuracy (or related measures), which does not necessarily generate data close to the real underlying distribution. We prove a simple Gibbs Sampling implementation to generate artificial data and balance the dataset respect to the class value; this method is a combination between Monte Carlo Integration, Markov Chais, and the Accept Reject Sampling. The proposed approach generates a sample that maximizes the objective function, and the objective function is built from the minority class if the dataset. The literature related to Monte Carlo Markov Chains assures that these types of methods preserve the underlying data distri-bution. The proposed approach generates artificial data keeping the underlying dataset distribution.

A New Hybrid Evolutionary Algorithm for the Treatment of Equality Constrained MOPs

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Evolutionary multi-objective optimization (EMO) is certainly a story of great success considering the numerous contributions and their applications to different problems and fields during the last two decades. One issue, however, that has been almost neglected so far is the consideration of multi-objective optimization problems (MOPs) that contain equality constraints. Such constraints play a special role as the inclusion of each equality constraint typically reduces the dimension of the search space by one. Consequently, the probability for a randomly chosen candidate solution of an equality constrained MOP to be feasible is zero, which makes the treatment of such problems very hard for EMO algorithms.
In this paper, we argue that multi-objective evolutionary algorithms hybridized with continuation-like techniques lead to fast and reliable numerical solvers. For this, we first propose three new problems with different characteristics that are indeed hard to solve by evolutionary algorithms. Next, we propose a variant of NSGA-II with a continuation method. Numerical results on several equality constrained MOPs to show that the resulting method is highly competitive to state-of-the-art evolutionary algorithms.

Δ_p- Newton Method for Unconstrained Optimization

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In many applications, the problem arises that several objectives have to be optimized concurrently, leading to a multi-objective optimization problem (MOP). One important essencial feature of a MOP is that its solution set, the Pareto set, typically forms an object of dimension $k-1$, where k is the number of objectives involved in the problem. For the performance assessment of multi-objective evolutionary algorithms (MOEAs) so far, some performance indicators have been proposed. Since each of these indicators assigns a real number to any population (or any other subset of the domain of the problem), they also induce several scalar optimization problems defined on the MOEA populations. In this work, we present the Δ_p-Newton method, i.e., the population-based Newton method using the averaged Hausdorff distance Δ_p as the performance indicator. Theoretical results will show that one can expect local quadratic convergence toward the optimal population, which will be underlined by some numerical results.

A Novel Gradient Free Local Search Operator for Constrained Multi-objective Optimization

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Multi-objective evolutionary algorithms (MOEAs) are a widely accepted choice for the numerical treatment of multi-objective optimization problems (MOPs). For constrained MOPs, these methods still have room for improvement to compute satisfactory approximations of the solution sets. A possible remedy is the hybridization of MOEAs with specialized local search mechanisms; which is not a simple task since the high cost of them. In this work, we consider the constraints information when performing the local search, and propose a new and effective way to compute descent directions for constrained problems. Since the directions are computed via neighborhood sampling, the method is perfectly suited for the use within MOEAs or any other population based algorithm as the samples can be taken precisely from the populations. The new method can be used as local search engine within, in principle, any MOEA. Numerical results on some benchmark problems support the benefits of the novel approach. This work represents an important step to formalize gradient-free multi-objective descent directions and its efficient interleaving into MOEAs.

Multi-objective Evolutionary Algorithms from the Mathematical Programming Point of View

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Evolutionary multi-objective optimization is a story of huge success which has a huge impact in finance and industry. However, until now such multi-ob jective evolutionary algorithms (MOEAs) need quite a few function evaluations to obtain acceptable Pareto set/front approximations. One remedy to overcome this issue is to hybridize MOEAs with local search strategies. 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-ob jective optimization problem (MOPs) are 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 will consider multi-objective stochastic local search (MOSLS) from a more theoretical point of view. Simple considerations show that both pressure toward and along the Pareto set is already inherent in MOSLS for unconstrained MOPs which explains one facet of the huge success 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 which we demonstrate on some first numerical results.

Robot Arm Motion Planning with a Multi-Objective Algorithm

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Motivated with the idea that the motion planning problem for a robot arm with more than two forearms has not an closed form solution, here it is presented a multi-objective solution of this problem. That I am going to present here is a toy example about how multi-objective optimization can be used to solve this problem. Given a robot arm with n forearms, with $n > 2$ (with more than two forearms), the problem to move the "robot hand" from a position $\mathbf{p}_1$ to a position $\mathbf{p}_2$ is defined as:

$$
\begin{aligned}
\text{Minimize:} \quad & \sum \theta_i, \text{ and} \\
& \sum w_i \theta_i, \text{ for } i = \{1, 2, \ldots, n\} \\
\text{subject to:} \quad & \|\mathbf{p}_2 - \mathbf{p}_1\| < \epsilon,
\end{aligned}
$$

This is, the sum of the robot movements, measured as angular displacements, is minimized. The second objective helps to explore the search space and to generate a set of solutions to the problem. This bi-objective problem with a single constraint is solved using NSGA-II algorithm. As an example, the 2D robot in Fig. 1, with forearm widths $\{100, 90, 80, 50\}$, and initial angles $\{60°, 10°, -20°, -20°\}$, weights $\{10.0, 5.0, 1.0, 1.0, \}$ which give the initial hand position $\mathbf{p}_1 = [175.5, 257.5]$, is desire to be moved to position $\mathbf{p}_2 = [244, 172]$. Here the value of $\epsilon = 4$ is used. The Pareto front of the solutions of 10 independent runs is shown in Fig. 2. The Pareto front with 10 incremental solutions –the previous output is used to start the algorithm, the initial solutions are random– is showed in Fig. 3. For all the runs a population of 100 individuals and 500 generations were used. This similar methodology was also used to solve a robust ellipse fitting [1] problem.

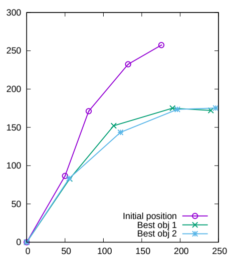

Fig. 1. Robot in the initial position and the two extreme solutions in Fig. 3

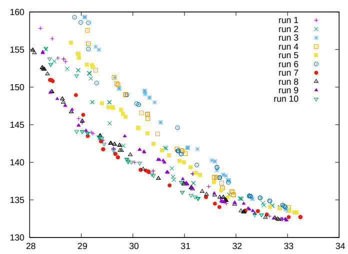

Fig. 2. Pareto front of 10 independent solutions.

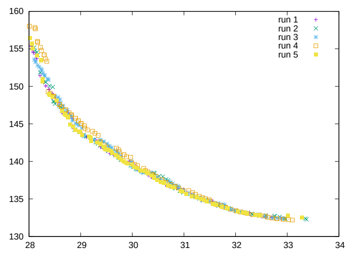

Fig. 3. Pareto front of 5 incremental solutions.

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Robotics State Machine Behaviors Derived with Genetic Algorithms

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***Abstract*— In this work, we propose the use of genetic algorithms to evolve finite state machines (EFSM) to generate reactive behaviors for mobile robots . We build these models using a modified version of FSMs and we propose an optimization process using genetic algorithms to find the best behavior for a mobile robot to avoid obstacles while it goes to a destination. We first train our EFSM in a simulated environment and then test the best model in a number of unknown scenes. We compare our algorithm with a human made FSM, where we show that the evolutionary approach outperforms it.**

I. Introduction

Behaviors are commonly used for mobile robots navigation [1] and they can be implemented using algorithm state machines (ASM). Figure 1 shows an example of a behavior for avoiding obstacles: a robot with two sensors S_L and S_R (left and right) to detect obstacles that performs four different movements depending on what is detected. Figure 2 shows the corresponding ASM to implement this behavior. There

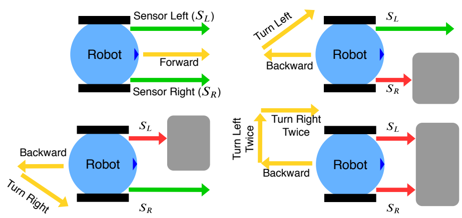

Fig. 1. Obstacle avoidance behavior.

are several options for the physical implementation of ASMs. In this work we propose an architecture (shown in figure 3) based on standard memories. In this architecture, an ASM is encoded in a look-up table that contains the next state and outputs for each state. The ASM inputs (given by sensors) and the next state are concatenated to form the memory address that contains the next state and outputs for the present state. Using this method, each state is represented by $N_b = \lceil log_2(N_s) \rceil$ bits where N_s is the number of states. The number of memory locations needed is given by $2^{(N_s+N_i)}$, where N_i is the number of inputs.

Figure 2 shows an ASM with 12 states and 2 inputs. For this ASM, four memory locations are used to represent each state and the total number of memory locations is 64 (upper power of two). Table I shows the memory data needed to

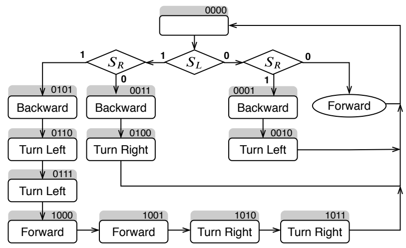

Fig. 2. ASM for a mobile robot that avoids obstacles.

encode the state 0000 of such ASM. Inputs S_L and S_R represent the digital values of sensors, whose state is 1 when there is an obstacle in front of them and 0, otherwise. ASM outputs are encoded with 6 bits. 2 bits are used to indicate the direction (DIR) that the robot should follow: 00 forward; 01 turn left; 10 turn right and 11 backward. Another 4 bits are used to indicate the magnitude of the command: for translations, it indicates the distance that the robot will move forward or backward and for rotations, indicates the angle that the robot rotates, with a maximum value of $\pi/2$ [rad] corresponding to 1111. In state 0, the conditional output *Forward* (shown inside the oval in figure 2) is generated when both inputs S_L and S_R are equal to 0. For the other cases the robot will stop, thus the magnitude is 0000.

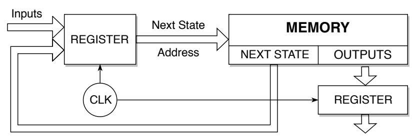

Fig. 3. Implementation of an ASM using memories.

As we can see in table I, if some of the bits in the memory content of this table are changed, then the robot behavior will also change. The main goal of this work is to find the best configuration of the memory content to get a behavior that avoids obstacles while it tries to reach a destination which, in this case, is given by a light source.

II. Genetic Algorithm for Finding Navigation Behaviors

In this work we use the Eclectic Genetic Algorithm (EGA) [2] to automatically generate a navigation behavior (given

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MEMORY ADDRESS		MEMORY CONTENT		
Present State	Inputs	Next State	Outputs	
ABCD	S_L S_R	ABCD	DIR.	MAGNITUDE
0 0 0 0	0 0	0 0 0 0	0 0	1 1 1 1
0 0 0 0	0 1	0 0 0 1	0 0	0 0 0 0
0 0 0 0	1 0	0 0 1 1	0 0	0 0 0 0
0 0 0 0	1 1	0 1 0 1	0 0	0 0 0 0

TABLE I
MEMORY DATA FOR STATE 0 SHOWN IN FIGURE 2.

by an ASM) that allows a mobile robot to navigate in an environment avoiding obstacles. The GA finds a set of next states and outputs, associated to each state, that form the behavior: $B = \{s_1o_1, ..., s_io_i, ..., s_ko_k\}$. The robot's behavior is encoded in the look-up table content as the one shown on table I. General steps for evolving behaviors are:

1. A population is generated randomly, with L individuals $B_1, B_2, ..., B_L$, in which each individual's chromosome is a string of binary numbers that represents the behaviors $B_i = \{011011...0101\}$. The string is separated into small segments that represent the next states and the outputs together, $\{s_i, o_i\}$. Depending on the number of states N_s, each next state s_i is represented by $N_b = \lceil log_2(N_s) \rceil$ bits.

2. Each individual (chromosome) is evaluated with the following criteria: distance between goal and last position reached (d_g), number of times the robot hits an obstacle (n_o), number of steps needed to reach the goal (n_g) and the number of times the robot went backwards (n_b). The proposed fitness function for the i-th individual is given by

$$F_i = \frac{K_d}{d_g + 1} + \frac{K_o}{n_o + 1} + \frac{K_g}{n_g + 1} + \frac{K_b}{n_b + 1}$$

where constants K are chosen according to the desired robot performance. For instance, if it is desired that the final robot's behavior goes backward only few times during navigation, then K_b should be several times bigger compared to the other constants.

3. Best individuals are selected according to their fitness function and a new population is generated through evolutionary operators (selection, crossover and mutation).

4. The offspring and their selected parents form the new population.

5. Steps 2 to 4 are repeated for N generations or until the difference of the overall fitness criteria between two generations is less than a given ϵ. Resulting behavior is an Evolved Finite State Machine (EFSM).

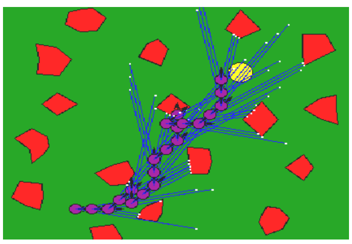

Fig. 4. EFSM tested on a simulated environment.

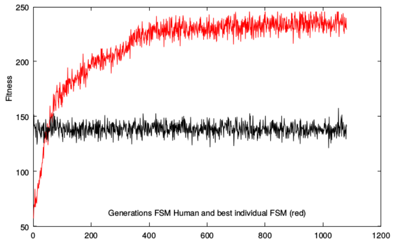

Fig. 5. Fitness of the EFSM (red) and the Human FSM (black).

III. EXPERIMENTS AND RESULTS

The algorithm to avoid obstacles was tested in a simulated environment shown in figure 4, where the goal destination is described by the yellow circle, free space is colored green, obstacles are described by polygons in red, robot is the purple circle and the proximity sensor readings are represented by blue lines.

Sensor readings are simulated by calculating the distance between the robot and objects in front of it. Gaussian noise is added to these values. Each EFSM has 16 states (4 bits); two obstacle avoidance input sensors (2 bits); one sensor that indicates the intensity of a light source (1 bit) and one sensor that indicates the quadrant where a light source is located (two bits). The EFSM has 6 outputs (3 bits). The total memory used to represent the algorithm behavior was 512 locations each one with 7 bits. Thus, it is required 3584 bits per individual's chromosome.

For the genetic algorithm, we had a population of 100 individuals and the evolution lasted 1,000 generations. Each generation was tested with 10 different environments with an area of $4m^2$ and 30 random obstacles. For each environment, behavior was tested with 20 origin/destination points. In total, 10,000 environments were created with 200,000 origin/destination paths that the simulated robot needed to follow.

To compare the performance of the EFSM, we used as baseline a FSM tuned by a human. Figure 5 shows the fitness functions for each generation of the human FSM and the best EFSM evolved by the GA. As we can see the best performance is done by the EFSM generated by the GA.

IV. CONCLUSIONS

An obstacle avoidance robot's behavior was found automatically using genetic algorithms, we proved that GA is a good option as a method for finding behaviors for mobile robots' navigation. Our experiments proved that the EFSM outperforms the human FSM.

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Machine learning, fault detection in wind turbine blades and related databases: A review of the state-of-the-art

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Abstract

The kinetic energy of wind can be conveniently converted into electricity using large wind turbines located in wind farms that can exceed 100MW of total energy production. Wind is one of the main renewable sources of energy that has reached a greater degree of maturity in European and American countries, especially established on onshore in areas where the wind proliferates [1]. Likewise, the development of offshore wind generation parks is also proliferating, with differentiated characteristics compared to land facilities - the wind resource at sea is superior (greater use of the installation), the impact visual and acoustic is less [2]. The wind turbines, consist of large blades ranging from 40 to a little over 100 meters in length, these blades are in direct contact with the wind and because of their size are susceptible to suffer structural damage caused by natural phenomena such as the wind itself, rain, hail, an other such [3][4]. These damages range from erosion, delamination, bending and other forms of deformations that can lead to losses in energy production, as well as economic losses generated by corrective maintenance or replacement of blades [5]. In this work, we will present a survey on the state of the art related to the diagnosis of the structural health of the blades using machine learning techniques, a new and promising research line. Using machine learning, it may be possible to detect, or maybe even predict, damage to the blades and facilitate corrective and preventive measures. This work will also provide a brief analysis of public datasets that have been made available to promote research in this domain. Our ultimate goal is to develop new learning methodologies specifically tailored for this important application.

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Modeling of the dynamic response in a gas turbine using experimental vibrations with machine learning

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Abstract

Electric power is often generated with gas or other fossil fuels. The gas activates mechanical components in a turbine to carry out the generation process. These mechanical components tend to fall over time, causing losses and increasing corrective maintenance costs. This paper presents the analysis and modeling of the vibrations of a gas turbine using the speed of the system and data obtained during the start up process until reaching the nominal speed for power genration. A study was carried out where a vibration analysis of the bearing mounted between the shaft and the compressor was carried out, which is associated with the speed of the turbine. The relation between the vibration and the speed of the turbine is studied using data collected from a particular model of gas turbine.

We propose a computational modeling following a supervised learning approach implemented through different machine learning alternatives, namely: i) multilayer perceptron neural networks (MLP); ii) Support Vectors Machines (SVM); iii) random forests (RF) and iv) genetic programming (GP) with local search. Results show that all methods are capable of modeling the vibration of the turbine, and that these models could be used to detect anomalous responses of the system during startup.

Pareto Explorer for Finding the Knee for Many Objective Optimization Problems

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In many areas such as Economy, Finance, or Industry, the problem arises naturally that several conflicting objectives have to be optimized concurrently. Such problems are called Multi-objective Optimization Problems (MOPs) in literature. The solution set of a MOP (in decision space) is called the Pareto set and its image (defined in objective space) the Pareto front.

Recently, MOPs with more than four objectives, which are also termed as Many Objective Optimization Problems (MaOPs), have caught the interest in Industry due to the decision-making processes are getting more and more complex. In particular, a lot of applications require finding the solution with an adequate trade-off between all the objectives. The knee of the Pareto front usually provides such a point. In [1], we can find a mathematical definition of the knee and a procedure, based on the NBI algorithm, to get it.

In this work, we use the novel Pareto Explorer framework [2] for finding the knee of MaOPs. We also prove the equivalence of the knee definition of [1] with the proposed approach. Finally, we demonstrate the advantages of our proposal with several examples.

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A Benchmark for Equality Constrained Multi-objective Optimization

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Evolutionary multi-objective optimization (EMO) is certainly a story of great success considering the numerous contributions and their applications to different problems and fields during the last two decades. One issue, however, that has been almost neglected so far is the consideration of multi-objective optimization problems (MOPs) that contain equality constraints. Such constraints play a special role as the inclusion of each equality constraint typically reduces the dimension of the search space by one. Consequently, the probability for a randomly chosen candidate solution of an equality constrained MOP to be feasible is zero, which makes the treatment of such problems very hard for EMO algorithms. In this paper, we propose a new benchmark of equality constrained MOPs. The problems are derived from the well-known DTLZ and IDTLZ problems and hence inherit their properties. The new benchmarks, Eq-DTLZ and Eq-IDTLZ, are scalable both in decision and objective space as well as in the number of equality constraints. Furthermore, all Pareto sets differ from the solution sets of the unconstrained problems and can be expressed analytically which make them good candidates for testing EMO algorithms on this important problem class. Based on the new benchmark, we investigate the performance of some state-of-the-art evolutionary algorithms. The results show that the new problems are indeed hard to solve for all considered algorithms and that further investigation has to be done for the reliable treatment of equality constrained MOPs.

The Pareto Tracer for General Inequality Contraints

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e Pareto Tracer (PT) is a recently proposed continuation-like strategy that is capable of perform
novement along the set of Karush-Kuhn Tucker (KKT) points of a given continuous multi-object
imization problem (MOP). So far, however, the PT only can handle equality and box constraints.
this presentation, we will show how to modify the PT so that it can also efficiently handle gene
quality constraints. We will demonstrate the efficiency of the new method both on some benchm
ctions as well as on some real-world applications where inequalities occur.

Implementation of Genetic Programming with Geometric Semantic Operators in GPU

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In this work a Geometric Semantic Genetic Programming (GSGP) algorithm was proposed and implemented in GPU to solve optimization problems. The solutions are searched in the semantic space described in [1], in which the main stages of evolution are transformed into operations with semantic matrices. The whole Genetic Programming (GP) population is evaluated by means of a CUDA kernel function in which each individual is mapped to a GPU thread applying the execution model of a Single Instruction Multiple Threads, the interpreter used is similar to the one proposed in [2]. One of the pioneering works in GP in GPU was Robilliar described in [3], where they propose an execution scheme for GP known as ThreadGP and BlockGP which is the definition of the execution unit for the CUDA kernel of some GP operation in the GPU. The geometric semantic stage is processed through CUDA kernel in collaboration with a set of processor streams that vary in each GPU, the execution scheme of this stage is adapted automatically taking into account the size of the population and the number of fitness cases which allow us to implement a SIMD model for the parallelization of semantic matrices. This proposal was widely evaluated with synthetic data to determine the acceleration of this implementation with respect to its sequential version, the results obtained show a speed up 700 using a Quadro P4000 GPU.

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A Multi-Objective Design for Finding High Nonlinear S-boxes

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Abstract

Substitution Boxes (known as S-Boxes) are the main element of the current Block Ciphers used to secure digital information in Cryptography. They are the only element that provides nonlinearity to the ciphers. As a consequence, the selection of strong S-Boxes with good cryptographic properties is quite important to offer security.

S-Boxes can be considered as boolean functions with n-bit input and m-bit output, denoted as $S : \{0,1\}^n \to \{0,1\}^m$. For the case of $m > 1$ they are considered as vector boolean functions, which is the case for actual S-Boxes. Only few functions out of the candidate set can to be used as S-Boxes. Different aspects must be considered when selecting S-boxes, for instance, nonlinearity, balance, algebraic degree, immunity coefficient, among some others.

To design S-boxes is a complicated task, mainly because the huge size of the search space, but also because some of the aspects to be optimized are in conflict to each other. An important body of research has been conducted using Evolutionary Algorithms for designing strong S-boxes, however the results are not good enough when compared against those found with algebraic tools. Actually, according to [1] algebraic constructions give unsurpassed results with regards to all the properties. Despite that, some recent research has been conducted with some improvement in the results.

In this work we present the statement of different multiobjective fitness functions for maximizing the nonlinearity of large S-boxes through an Evolutionary Algorithm.

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Analysis of Differential Evolution variants for parameter tuning of Decision Trees inductive algorithms

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This paper presents an empirical comparison of some Differential Evolution variants to solve the parameter tuning of Decision Tree induction algorithms. The aim of this analysis is to identify which one of the variants is more competitive to this problem. In this work, an EVolutionary Agents & Artifacts approach for the induction of Decision Trees (eva2dt), is adopted to maximize the classification accuracy.
The Agents & Artifacts paradigm [6] naturally accommodates the concept of an evolving population of agents inducing and evaluating decision trees, using different tools implemented as Weka-based artifacts [1]. The use of different inductive algorithms, instead of a single one, is a novelty with respect to related work [2, 4, 3]. Eva2dt agents represent potential solutions for the Differential Evolution algorithm [5], which are mapped to parameters for inductive algorithms, e.g., j48, SimpleCART, RepTree and RandomTree. Each agent is able to induce decisions trees and to also compute their accuracy through a 10-folds cross-validation process.
The assessed Differential Evolution variants vary in the recombination operator adopted and in some self-adaptive mechanisms. A set of statistical tests were performed to validate the obtained results. All variants were tested on 16 public datasets, obtaining competitive results, particularly for the datasets with the fewer number of training instances. Preliminary results suggest that DE/rand/1/bin variant outperform the others, even when more generations are added. These observations will help to develop other mechanisms to improve the current performance (convergence and final accuracy).

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Application of multiple preference incorporation approaches to solve dynamic multi-objective optimization problems

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A dynamic multi-objective optimization problem (DMOP) is a problem which has multiple objectives to improve, and that is within an environment that changes over time. A typical situation when solving optimization problems is that there is an agent in charge of making decisions, called decision maker (DM). The DM usually focuses on a region of interest (ROI) within the solution space. Within the literature, there are multiple proposals to solve problems with built-in preferences. However, few of these works focus on a dynamic environment [1–4].

We propose in this article the study of several dynamic multi-objective evolutionary algorithms (DMOEA) with specific preference incorporation techniques added which follow different approaches, classified in [5]. This paper studies reference-point and weight-based approaches.

RNSGA-II focuses its search by directing current solutions to one or multiple reference points [6]. We insert change detection and adaptation methods based on DNSGA-II [1] into RNSGA-II (DRNSGA-II) to adapt it for solving DMOPs. The Concordance-based Preferential Genetic Algorithm (CPGA) is a DMOEA that incorporates preferences based on a concordance criterion between each solution pair based on a set of preferential weights established by the DM.

In a dynamic environment, there could be issues when using preference-point-based approaches. As there is a risk that these points might not represent the DM preferences after a change. Also, weight-based approaches could require constant recalculation after an environmental change as the current weight vector might lead to solutions outside of the ROI under the new problem setting. This paper studies a method of incorporating preferences, called Plane Separation (PS), which allows generating reference points based on the information given by a population and a weighting coefficient assigned to each objective. PS is inserted into several DMOEAs, DNSGA-II-A, DNSGA-II-AB [1], CPGA, as well as dynamic versions of GDE3 [7] (DGDE3-PS) and SPEA2 [8] (DSPEA2-PS).

These algorithms are tested in several instances from the FDA [9] and dMOP [10] test suites. For all DMOPs, the defined change severity and frequency are 10 time steps and 25 generations, respectively. All DMOEAs have a population of 100 individuals and an archive of the same size in the case of DSPEA2-PS. Since all tested DMOPs are bi-objective, the DM preferences focus on high and low values for f_1. All DMOEAs use simulated binary crossover with 0.9 probability as crossover operator, and polynomial distribution with $1/n$ probability, where n is the number of variables of a DMOP, as mutation operator [11]. The given distribution indexes are 10 for crossover and 20 for mutation. DGDE3-PS follows a rand/1/bin setup with both crossover operation and mutation scaling factor set as 0.5.

Table 1 shows the offline median (average of all time steps) and standard deviation for hyper-volume ratio (HVR) [12] obtained by some of the proposed DMOEAs: CPGA, DRNSGA.II, DNSGA-II-A-PS, DNSGA-II-AB-PS and DGDE3-PS for all tested DMOPs when the DM introduces a preference towards low values for f_1, in this case, 10% and 40% of the range between the minimum and maximum value of f_1.

Table 1: Offline median and standard deviation of HVR preference towards $f_1 = [0.1, 0.4]$

Problem	CPGA	DRNSGA-II	DNSGA-II-A-PS	DNSGA-II-AB-PS	DGDE3-PS
FDA1	5.646E-1(3.768E-2)	6.321e-01(2.123e-02)	*6.555e-01(1.741e-02)*	6.511e-01(3.902e-02)	6.176e-01(1.573e-02)
FDA3	8.547E-2(3.908E-2)	3.159e-01(2.974e-02)	3.095e-01(8.590e-02)	3.037e-01(1.152e-01)	*3.264e-01(1.040e-02)*
dMOP1	7.759E-1(4.461E-2)	8.442e-01(5.021e-02)	8.517e-01(3.331e-02)	8.495e-01(3.302e-02)	*9.089e-01(1.043e-02)*
dMOP2	3.343E-1(1.166E-1)	7.842e-01(1.234e-02)	8.506e-01(2.586e-02)	*8.607e-01(2.805e-02)*	8.588e-01(5.065e-03)
dMOP3	7.733E-1(4.124E-2)	8.848e-01(9.544e-03)	*9.293e-01(1.580e-02)*	8.918e-01(3.263e-02)	9.214e-01(9.006e-03)

Considering the presented results, DNSGA-II-A-PS performs better than the other displayed DMOEAs for FDA1 and dMOP3. Both instances have a similar characteristic, as their optimal POF never changes. Meanwhile, DGDE3-PS and DNSGA-II-AB-PS are the most effective alternatives for the rest of the DMOPs, which have optimal POFs that change as time progresses. These preliminary results allow us to imply that the application of preference incorporation methods that combine the weight-based and reference-point approaches can be effective for dynamic optimization problems. Also, this new approach allows both the DM and the people in charge of preference modeling to work multiple problems with different characteristics without requiring problem-specific information.

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Multi-objective optimization of a flock of robots for location tasks.

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A policy for coordination of a flock of robots based on repulsion, attraction, orientation and influence is proposed. Establishing a location task, several objectives are required to maintain swarm properties of the flock (aggregation, , flocking, avoid collisions) and increase performance of the flock performing the task (minimum time, all members arrive at the same time) Considering four objective functions a NSGA 2, a MoEAD and a MOPSO, a Pareto from are generated using a model to represent the functioning of the simulator to accelerate the evaluations. Pareto fronts are generated with four objective functions and repulsion with attraction plays an important role for increasing performance of the flock performing task assigned.

Multi-Objective Optimization using Decomposition: The Case of the Whale Optimization Algorithm

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Whale Optimization Algorithm (WOA) is a nature-inspired metaheuristic which has been recently proposed for solving global optimization problems. This algorithm is inspired by the hunting strategy and social behavior of humpback whales. This algorithm has gained popularity in the last years for its ability to solve complex optimization problems. In this work, we extend the use of WOA to deal with multi-objective problems using a decomposition approach. In this way, our proposed WOA algorithm approximates the Pareto front of a multi-objective problem by solving a set of scalarizing subproblems in which the problem is decomposed. Our multi-objective WOA algorithm is compared against traditional decomposition-based multi-objective evolutionary algorithms adopting a set of multi-objective problems with complicated Pareto fronts. Preliminary results indicate that our proposed WOA algorithm is a viable choice to efficiently solve optimization problems with multiple objectives.

NONLINEAR ANALYSIS FOR A TYPE-1 DIABETES MODEL FOCUS ON T AND β CELLS BEHAVIOR

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Type 1 diabetes is an autoimmune disease in which the cells of the pancreas do not produce enough insulin, a hormone which helps use blood sugar (glucose) for energy [1]. It is estimated for the year 2050; diabetes will significantly impact not only on the worldwide mortality rate but also on a substantial economic investment related to insulin treatments and other issues that are attached to this disease [2]-[4]. Therefore, a broader understanding on how the immunological immune response via autoreactive T cells is involved in the destruction of pancreatic beta cells (β-cells) leads on how a treatment or therapy can be defined in order to prevent the decay on the regular insulin proliferation rate.
The numerical approach is commonly used to understand a broader and general interaction between glucose and insulin rates due to chaotic behavior of the studied model [5]; the only disadvantage of this strategy is the accuracy on defining the maximum carrying capacity for each variable due to the linear approach in which the analysis holds. Therefore, the mathematical analysis present in this work relays in the application of nonlinear control theory in order to defined maximum carrying capacity for each variable establishing a positive bounded invariant domain by applying the Localization Theorem and the Iterative Theorem presented in [6, 7]. A Thau observer is developed to estimate, in long periods on how β-cells will behave in the scenario where are labeled as antigen cells. Moreover, an adaptive sliding mode control is taking on to suppress the chaotic oscillations to achieve stability for an arbitrary unstable equilibrium point or periodic orbit.
The mathematical model that is analyzed is described in [8], where it is defined by fifth-order differential equations where is involved the interaction of resting macrophages (M), activated macrophages (M_A), antigen cells (A), autolytic T-cells (T), and β-cells (B) as following

$$\frac{dM(t)}{dt} = a + (b+k)M_A(t) - cM(t) - gM(t)A(t); \tag{1}$$
$$\frac{dM_A(t)}{dt} = gM(t)A(t) - kM_A(t); \tag{2}$$
$$\frac{dA(t)}{dt} = lM_A(t) + qB(t)T(t) - mA(t); \tag{3}$$
$$\frac{dT(t)}{dt} = s_t + sM_A(t)T(t) - \mu_T T(t); \tag{4}$$
$$\frac{dB(t)}{dt} = s_B - qB(t)T(t) - \mu_B B(t). \tag{5}$$

Where in equation (1) the recruitment rate of macrophages and the last term represents the rate at which macrophages become activated due to interaction with antigenic proteins. Equations (2)-(3) represent the dynamics of activated macrophage population and the antigenic peptide concentration, respectively, in with the first term of equation (3) represents an increase due to antigenic peptides released by activated macrophages. The dynamics of autolytic T-cells, which are a subset of helper T-cells is modeled by equation (4) and equation (5) the dynamics of the β-cell population.

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Hardware implementation of the phase distortion to amplitude conversion algorithm applied for a 1.84-GHz PA

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In this work, a phase-to-amplitude conversion algorithm is implemented in hardware to evaluate the amplitude-to-amplitude (AM-AM) and amplitude-to-phase (AM-PM) distortion curves of a 1.84 GHz 5W RTD233PD radio frequency (RF) power amplifier (PA). The system involves a modelling stage of a real-world systems related to wireless signal transmission, the system was implemented on the FPGA Cyclone V development board by using a 14 bit data acquisition card. The accuracy obtained in the modelling stage below -53.5 dB Normalized Mean Square Error (NMSE) and the Root-mean-square (RMS) error of 0.02 during the phase detection, allow us to think about an efficient proposal to replace the expensive equipment as the vector network analyser (VNA) used traditionally to measure a RF-PA behaviour given by the S21 parameter measurement that shows the offset of the output signal with respect to the input in order to estimate the AM/PM distortion curve. In this work a complete scheme is developed in Matlab/Simulink based on the DSP Builder design tool that improves the reported precision alternatives reported in literature. In the Figure 1 is depicted the whole system developed on Simulink to generate the synthesizable code that generate the Register Transfer Level (RTL) code on Quartus program.

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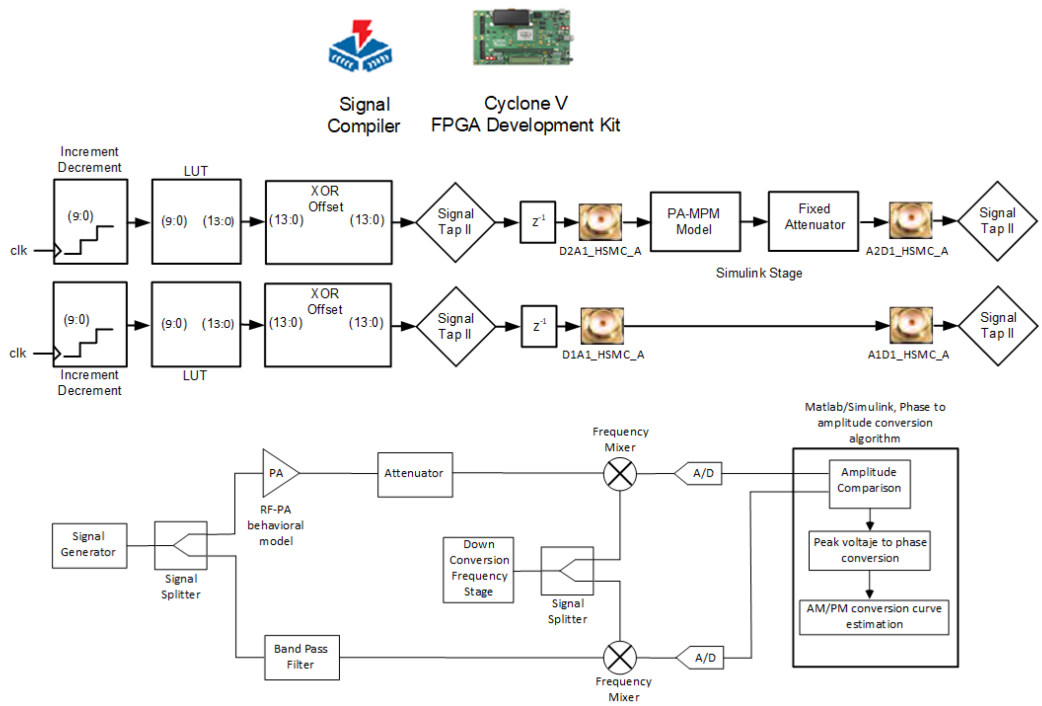

Figura 1: Acquisition system for AM/AM and AM/PM conversion curves for the 5W RTD233PD @ 1840MHz RF-PA.

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The Design of Graphical User Interfaces through Automatic Optimization Methods: A Review of the State of the Art

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Abstract

The design of intuitive Graphical User Interfaces (GUIs) is not a simple task for designers, it requires the understanding of the cognitive processes and resources that the user uses in the process of Interaction with GUIs; as well as the appropriate selection of colors, labels, buttons, icons and procedures, based on the knowledge and experience of the users. The User-Centered Design, is a process that contemplates a set of methods and techniques that help to design usable GUIs, however, the result will depend on the knowledge and experience of the designers, which means that they still used their techniques and methods the results will not be the same for different designers. In order to explore additional ways to accelerate the design cycle and find the most optimal design in terms of usability with any designer, a review of related works using automatic optimization methods for GUI design is presented.

Keywords: Design, Graphical User Interfaces, Usability, Automatic Optimization.

Visual–Inertial Odometer with a Marker

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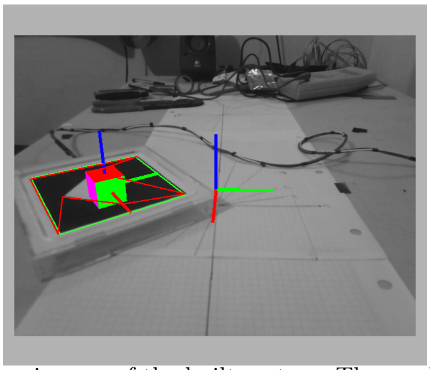
It is possible to have a vision system to recognize and to track the position and orientation (the pose) of a fiducial marker based in order type [1, 2]. These fiducial markers have the advantage that the point correspondences can be solved at the same time that its point features are detected. This visual system is slow, it can work at 30 frames per second, or less if the marker is occluded. Also, there are low cost Inertial Measurement Units (IMUs) that can work to high speeds up to 1 KHz. In this way we present a visual-inertial tracking system working in a Single Board Computer Raspberry Pi version 3. The system has integrated an extended Kalman filter to control the data fusion. Two images of the built system are shown in Fig. 1.



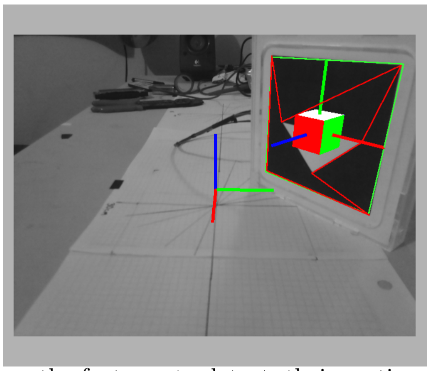


Fig. 1. Two images of the built system. The marker has triangles as the features to detect, their vertices positions are the marker's points. The IMU is attached behind the marker. Each axis x, y, and z are colored with red, green, and blue lines, and a virtual cube is draw on the marker coordinate system. It is also shown the initial marker position.

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Augmented Interaction with a Deformable Object

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We present an Augmented Reality system in which the user can interact in real time with solid and deformable models. The fingers positions are tracked by the Leap Motion device [1], the virtual objects are draw with respect to a fiducial marker [2]. The collision detection and the object's behavior based in physics are given by the Bullet Physics library [3]. Two images of the built system are shown in Fig. 1.

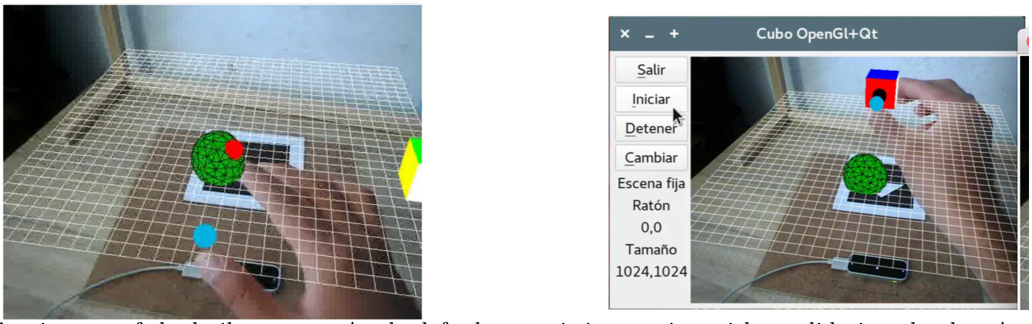

Fig. 1. Two images of the built system. At the left the user is interacting with a solid virtual cube. At the right the user is interacting with a deformable sphere. On each finger position a sphere is draw (in blue) with are the virtual interacting objects.

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Camera-Radar Data Fusion for Traffic Participants Detection in Intelligent Intersection System

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In last years Smart Cities have gotten interest from both science and industry [3] therefore the development of new technology in the field becomes a priority. In this sense, automotive industry is expanding the market away from autonomous driving cars by the inclusion of intelligent infrastructure. For example, communicate cars with the cloud in order to update status of the environment with information from sensors mounted on the traffic lights, lamps or signal poles located on the road side. In particular, intersections have gotten a lot of attention due to the challenges caused by the interaction between pedestrians, bicycles and vehicles. Here, accidents occurred because the participants do not have enough information to avoid wrong decisions. This problem will not be completely overcome by autonomous vehicles with their many sensors, therefore the missing information can be computed and broadcast via Infrastructure to Vehicle (I2V) network by the intelligent intersection [4, 2]. Hence, data from sensors like cameras and radars is used for the detection and tracking of the traffic participants, then the system broadcast an object list.

In the field of Advanced Driver Assistance Systems (ADAS) camera-radar fusion algorithms have been developed in order to solve problems like obstacle detection [7, 10], distance estimation [11] and object perception [8]. Otherwise, this work presents an approach to fusion data from cameras and automotive grade radars for infrastructure application. Traditional vision based object detection uses feature image extraction [9] and descriptor matching, these methods usually have poor real-time performance [1]. Otherwise deep learning methods have competitive accuracy and real-time performance such as object detection algorithms based on convolutional neural networks like You Only Look Once (YOLO) [6] or Single Shot Detection (SSD) [5]. The presented approach uses SSD for object detection in the image captured by the camera, as detection results classification and bounding box are obtained. Kalman Filter is used to fuse and track the objects detected by the radars while the camera data update the objects classification and the probability of existence.

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A new probabilistic segmentation method of lanes for autonomous vehicles

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Lane detection in driving scenarios is an important module for autonomous vehicles and advanced driver assistance systems. In recent years, sophisticated methods have been proposed. However, most methods focus on detecting the lane from a single image, which leads to unsatisfactory performance in situations with lighting changes or occlusions. Consequently, this thesis paper presents a probabilistic approach, using Kalman Filter, which allows the lane that cannot be detected in the current frame to be inferred by incorporating information from previous frames, considering uncertainty in the prediction as well as in the detection. Secondly, a principal component analysis of the segmented curvature is presented, with the purposes of dimensionality reduction, moving from a pixel space, to a reduced space of three parameters and thus reducing the computational cost.

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Index