出國報告（出國類別：出席國際學術會議）

出席「**2013 IEEE** 系統科學與工程國際研討會」

服務機關：國立台北大學 電機工程學系
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摘要(200-300 字)

「IEEE 系統科學與工程國際研討會」是一個每年定期召開的系統科學專業論壇，其意在促進專業領域學術交流與合作。本人此次於會議中安排有兩個報告，分別是第一天的口頭報告「Admissibility of fuzzy support vector machine through loss function」及第二天的海報張貼「Robust tracking controller design and its application to wheeled robot」兩篇論文與會，並以之與學者們交換意見，兩論文一為支持向量機基本性質的探討，另一探討機器人路徑跟隨控制器之設計，具皆為本人近年研究之成果。會議交流，亦從各與會學者的報告與交談中，獲得許多不錯的研究創意，在透過直接交換意見後，有些珍貴的想法。此行與眾多國際學者交流，開展國際視野，亦蘊釀一些國際合作的機會，收穫豐富。

目次

壹、 目的

研究工作本身並沒有國家的分界，而科學前沿的推進，除了有賴於國際期刊作為各國學者新近研究發表的平台外，傳統上，就是參加國際研討會，藉與會學者共濟一堂，來近距離交換意見，推動科學的進步。基於此，我準備了兩篇文章前往匈牙利參加「2013IEEE 系統科學與工程國際研討會」，除了發表論文，也著意於吸收新知，擴充國際視野，與一些具潛力有合作議題的伙伴，為在研究工作的生涯中，增加新動力。

貳、 過程

我與台北城市科技大學的鍾雅健老師於會議的前一天下午，在維也納會合後，搭火車抵達布達佩斯，並住進預定的旅館，準備參加隔天 ICSSE 舉辦的研討會。鍾教授在會議中發表了一篇文章，而我則有兩篇文章被安排在之後兩天的會議中發表。

翌日早上，我與鍾教授提早準備前往會場，但是因為交通不熟，且早上車流較多，大約晚了十分鐘才抵達 Óbuda University 會場，但還是來得及聽到會議主席 Rudas 教授致歡迎詞，及與會的貴賓的上台致詞，貴賓致詞完畢，開始會議行程。

此次會議的主辦單位安排有四個 Plenary talks: K. W. Hipel 教授的 Tackling climate change: a system of systems engineering perspective，李祖添教授的 Intelligent vehicles, H. Fujita 教授的 Decision making on medical diagnosis based on subjective and objective fuzzy aggregation functions alignment, W. A. Gruver 教授的 Distributed intelligent systems: technologies and applications。主題具皆貼近本會議的核心主軸 − 以系統為研究對象之研究，其中個人偏好前三場，主要是因本人亦從事機器人之駕駛與導航之研究相對的靠近李祖添教授所談的智慧車電。而第三場與第一場分別以醫學診斷及氣候變遷之主題，以系統工程的角度加以詮釋與探討，亦令人欣然嚮往。會間短暫休息，攝得照片 1。

由於系統工程研會早期是由台灣學者發起，而創立發展的。這次來自台灣的學者相當踴躍，我趁機會多認識一些與會的學者，有些是心儀許久而無交談過的優秀學者，藉機請益一些研究的看法及心得，獲益匪淺。平時在台灣可能大家都忙，倒來得異鄉，下了手邊的工作，才能盡其在我的暢談，真是咫尺天涯。

我在第一天的下午[T1c] Session on Knowledge-based Systems 有場報告(照片 2)，主題是 Admissibility of Fuzzy Support Vector Machine through Loss Function, 這是我在支持向量機研究上的一點小獲得，用來補充我之前計畫「支持向量機損失函數調控」(NSC 99-2221-E-149-009-)所提出新 Model 的一個基礎性質。

第一天會議結束，主辦的 Óbuda University 安排了一個多瑙河上的船上巡遊導覽，河上微微涼風佐以多瑙河畔著名城市布達佩斯的風景，令人陶醉。

第二天，我另有一個海報的 Session，大老遠背了這張海報周遊列國，今天出場(照片 3)，海報主題 Robust tracking controller design and its application to wheeled robot，是我與文化大學蘇國和教授有關機器人路徑跟隨的強健控制器設計研究的一個小作品。

在出發前，資策會的伙伴，給我一個訊息，我們有一個重要的廠商 Adaptive Recognition Hungary (ARH Inc.)正好也在布達佩斯。在伙伴的搭建的連絡管道下，我事先約好在第二天下午用短暫的時間去拜訪了這個公司，它是一個從事影像辨識的高科技公司，在專業領域其國際間知名度頗高。此次的拜訪，純粹是搭建友誼的拜訪，在我們的思考裡，密切的友誼是將來合作成功的基石。公司坐落在布達側山丘的南邊，從會場過去並不遠。我在該公司受到熱情的歡迎，除了原先約好的 Peter 以外，我也見到了 CEO Laszlo Kis 先生，相談甚歡，留下深刻的印象。

下午我回到會場，意猶未盡的再聽了兩場有關學者的論文，接著就是會議主席 Rudas 教授安排的一個外燴式的餐點，地點就在 Óbuda University 的一個寬敞的會議

場所裡。這是一個結束餐會，大家惺惺相惜，互相就專長與興趣的研究或學者交換意見及訊息，國際間因文化差異，思考不同，對於研究主題的想法不盡相同，在這種氣氛下的交談，常有意外驚奇的發現，足以筆記以為後來思考，而因此建立的友誼也相當地特別，期望有因此交會而迸出的火花。

附記: 本次出國行程, 除了主要參加 ICSSE 的會議之外, 本另安排於 6 月下旬在德國參訪 Volkswagen 汽車廠, 原與 Volkswagen 方面安排妥當時值東歐洪泛, 易北河淹水, 致對方取消行程。不過, 原安排去布達佩斯訪問 ARH Inc.的部分, 如期完成. 十分感謝

參、 心得及建議

系統科學本身所涵蓋的範圍本就十分廣泛，就個人認知其經常取用訊息分析、控制工程等之工具作一些具體的研究。「IEEE 系統科學與工程國際研討會」廣集國際間系統科學研究學者，年度集會，是難得的一個可以互相交流的論壇平台，以系統科學研究工具日益精良、而研究者能計算解析的能力日益複雜，其在領域內抑或是在領域外所探索的問題將日益深廣而及於過去無法解析的複雜系統，是一具前瞻而有前途之科學。以此觀之，其參與與交流的層面將會持續擴大，而國內控制工程學者有此真知灼見，於浪潮之先創立此研討會，其先見之明令人折服，而今跨出了亞洲，來到歐洲由匈牙利的 Óbuda University 及 Hungarian Fuzzy Association 來承辦，顯見其未來發展可期。本次會議原排有三天的會期，囿於時間與資源的限制而壓縮成為兩天，因此每一場次的報告略顯擁擠而倉促，是唯一可惜的地方。

來匈牙利開會之前，個人正好研讀了一些 TS fuzzy control、Fuzzy sliding control、及 Reinforcement learning 的文章，而正好聽到[T1b]及[F2b]兩個場次中各有相關的報告，溫故而知新，令人回味。[T2c]場次中一位年輕學者 K. Thorsen 所報告的 Control theoretic properties of physiological controller motifs，嘗試用控制工程的理論來解釋 physiological motif，其學理基礎強，我本身因上過一些系統生物學的課，看到這樣的連結覺得相當有趣而意義深遠，值得繼續加以深化。第二天某場次的一個主題 Modeling and analyzing defense-in-depth in arming systems，則是我在 Plenary talks 繼醫學診斷及氣候變遷之主題後，再看到系統科學的學理往外延伸應用到國防武器管理上，也是系統科學正在往各種應用層面擴張的實證。

布達佩斯本身是旅遊城市的關係，在交通及會後旅遊的安排上，比較不需要主辦單位特意安排，而只須聚焦在會議本身的業務，這使得主辦研討會不必那麼辛苦，也不必煞費苦心的安排只為了盡地主之誼，這一個模式可為我們借鏡，將來若有機會在我所服務的台北大學籌辦國際研討會，以此一模式將以較少的人力、物力來達到目的。

肆、 附錄

一、 會議議程

二、 發表論文全文一**: Admissibility of fuzzy support vector machine through loss function**

三、 發表論文全文二**: Robust tracking controller design and its application to wheeled robot**

四、 活動照片

July 4, Thursday

8:00 – 16:00 **REGISTRATION**

9:00 – 9:30 **OPENING CEREMONY** **Room F09**

9:30 – 10:15 **PLENARY SESSION I** **Room F09**

Tackling Climate Change: A System of Systems Engineering Perspective

Keith W. Hipel

University of Waterloo, Ontario, Canada

Session Chair: ***Imre J. Rudas***

10:15 – 10:30 **COFFEE BREAK**

10:30 – 11:15 **PLENARY SESSION II** **Room F09**

Intelligent Vehicles

T. T. Lee

Chung Yuan Christian University, Chung-Li, Taiwan

Session Chair: ***Shun-Feng Su***

11:15 – 12:00 **PLENARY SESSION III** **Room F09**

Decision Making on Medical Diagnosis based on Subjective and Objective Fuzzy Aggregation Functions Alignment

Hamido Fujita

Iwate Prefectural University, Iwate, Japan

Session Chair: ***János Fodor***

12:00 – 13:30 **LUNCH**

13:30 – 14:15 **PLENARY SESSION IV** **Room F09**

Distributed Intelligent Systems: Technologies and Applications

William A. Gruver

Simon Fraser University, British Columbia, Canada

Session Chair: ***József K. Tar***

14:20 – 15:40 PARALLEL SESSIONS

14:20 – 15:40 [T1a] SESSION on Image Processing and Robot System I — Room F09

Session Chair: ***Shun-Feng Su***

14:20 – 14:40 **Enhance Intelligence Video Surveillance with 3-D Information**

Yujen Chou[1], Bor-Chyun Wang[2] and Shun-Feng Su[3]
[1]NTUST
[2]China University of Technology CSIE
[3]National Taiwan University of Science and Technology EE

14:40 – 15:00 **Adaptive Dynamic Surface Control for Fault-Tolerant Multi-Robot Systems**

Yeong-Hwa Chang, Wei-Shou Chan, Cheng-Yuan Yang
Chang Gung University, Taoyuan, Taiwan, R.O.C.

Chin-Wang Tao
National I-Lan University, I-Lan, Taiwan, R.O.C.

Shun-Feng Su
National Taiwan University, of Science and Technology, Taipei Taiwan, R.O.C.

15:00 – 15:20 **Study on Content-Independent Feature Matching Systems for Container Images**

Guo-Rong Huang, Shun-Feng Su, QiJun Chen, Yi-San Lin

15:20 – 15:40 **A Classification System of Lung Nodules in CT Images Based on Fractional Brownian Motion Model**

Po-Whei Huang*, Phen-Lan Lin**, Cheng-Hsiung Lee*, C. H. Kuo*
* National Chung Hsing University, Taichung, Taiwan
** Providence University, Shalu, Taichung, Taiwan

14:20 – 15:40 [T1b] SESSION on Dynamic Estimation and Fuzzy System — Room F08

Session Chair: ***Wen-June Wang***

14:20 – 14:40 **Prediction and Sensitivity Analysis by TS Fuzzy Neural Network for Fungal Growth in Food Products**

Yu-Hao Chang*, Wen-Hsien Ho*, Hon-Yi Shi*, Jyh-Horng Chou**,***
* Kaohsiung Medical University, Kaohsiung, Taiwan
** National Kaohsiung First University of Science and Technology, Kaohsiung, Taiwan
*** National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan

14:40 – 15:00 **Leader-Following Formation Control of Multi-Robot Systems with Adaptive Fuzzy Terminal Sliding-Mode Controller**

Yeong-Hwa Chang, Cheng-Yuan Yang, Wei-Shou Chan
Chang Gung University, Taoyuan, Taiwan, R.O.C.

Chia-Wen Chang
Ming Chuan University, Taoyuan, Taiwan, R.O.C.

Chin-Wang Tao
National I-Lan University, I-Lan, Taiwan, R.O.C.

15:00 – 15:20 **Fuzzy Control Design for Nonlinear Interconnected Systems by Transforming the Interconnection into a Weighting Linear Term**

Wei Chang, Shan-Ju Yeh, Wen-June Wang, Ya-Ju Chang
National Central University, Jhongli, Taiwan, R. O. C.

15:20 – 15:40 **The People Number Estimation Based on the Embedded DSP System with Surveillance Camera**

Nai-Jen Li, Cheng-Feng Weng, Wen-June Wang
National Central University, Jhongli, Taiwan, ROC

Hsiang-Chieh Chen* and Pei-Jun Lee**
* Industrial Technology Research Institute, Hsinchu, Taiwan, ROC
** National Chi Nan University, Nantou, Taiwan, ROC

14:20 – 15:40 [T1c] SESSION on Knowledge-based Systems — Room F07

Session Chair: ***Yo-Ping Huang***

14:20 – 14:40 **A Guidance Law Design Using the Combination of ISMC and SDRE Schemes**
Yew-Wen Liang, Jun-Yu Chen, Li-Gang Lin
National Chiao Tung University, Hsinchu, Taiwan

14:40 – 15:00 **Smart Phone-based Fuzzy Modeling to Examine Facial Skin Quality**
Yo-Ping Huang, Yan-Zong Li, Chien-Chou Lin
National Taipei University of Technology, Taipei, Taiwan

15:00 – 15:20 **Admissibility of Fuzzy Support Vector Machine through Loss Function**
Chan-Yun Yang*, Gene Eu Jan**, Kuo-Ho Su**
*, ** National Taipei University, New Taipei City, Taiwan
*** Chinese Culture University, Taipei, Taiwan

15:20 – 15:40 **Fuzzy Regulation of DC-Bus Voltage for Solar Energy System**
Gwo-Ruey Yu, Jian-Fu Chen
National Chung Cheng University, Chiayi, Taiwan

14:20 – 15:40 [TP1] POSTER SESSION

Embedded 8-bit AES in Wireless Bluetooth Application
Chi-Wu Huang, Shao-Wei Kuo, Chi-Jeng Chang
National Taiwan Normal University, Taipei, Taiwan

Employing 2DoF PID Controllers to Improve Greenhouse Climate System Robustness
Eugen Horatiu Gurban, Gheorghe-Daniel Andreescu
”Politehnica" University of Timişoara, Timişoara, Romania

15:40 – 16:00 COFFEE BREAK

16:00 – 17:40 PARALLEL SESSIONS

16:00 – 17:40 [T2a] SESSION on Optimization — Room F09

Session Chair: ***Nicola Pio Belfiore***

16:00 – 16:20 **A Petri Nets and Genetic Algorithm-based Optimal Scheduling for Job Shop Manufacturing Systems**
Albert W. L. Yao, Y. M. Pan
National Kaohsiung First University of Science and Technology, Taiwan, R.O.C.

16:20 – 16:40 **Design, Optimization and Construction of MEMS-based Micro Grippers for Cell Manipulation**
Nicola Pio Belfiore, Matteo Verotti, Rocco Crescenzi and Marco Balucani
Sapienza University of Rome, Rome, Italy

16:40 – 17:00 **Parallel Genetic Algorithm for Periodic Vehicle Routing and Scheduling Problem**

P. Kurdel and J. Sebestyénová
Institute of Informatics, Slovak Academy of Sciences, Bratislava, Slovakia

17:00 – 17:20 **Trajectory Optimization and Optimal Control of Vehicle Dynamics under Critically Stable Driving Conditions**

Shaady Khatab, Ansgar Traechtler
Heinz Nixdorf Institute, Paderborn, Germany

17:20 – 17:40 **Traffic Condition Monitoring using Complex Event Processing**

Bogdan Târnaucă
Siemens Corporate Technology Romania, and Transilvania University of Braşov

Dan Puiu, Dragoş Damian
Siemens Corporate Technology Romania

Vasile Comnac
Transilvania University of Brasov

16:00 – 17:40 [T2b] SESSION on Image Processing System — Room F08

Session Chair: ***Cheng-Yuan Chang***

16:00 – 16:20 **Vision-based Controller Design with the Application to a 3D Overhead Crane System**

Lun-Hui Lee[*], Chung-Hao Huang[*], Sung-Chih Ku[**] and Cheng-Yuan Chang[**]
[*] Institute of Nuclear Energy Research in Taiwan, Taiwan
[**] Chung Yuan Christian University, Taiwan

16:20 – 16:40 **Marker Localization with a Multi-Camera System**

Dávid Szalóki, Norbert Koszó, Kristóf Csorba, Gábor Tevesz
Budapest University of Technology and Economics, Budapest, Hungary

16:40 – 17:00 **Realization of Affine SIFT Real-Time Image Processing for Home Service Robot**

Ying-Hao Wang, Hao-En Cheng, Chih-Jui Lin, Ri-Wei Deng, Hsuan Lee, Tzuu-Hseng S. Li
National Cheng Kung University, Tainan, Taiwan, R.O.C.

17:00 – 17:20 **Road Area Detection based on Image Segmentation and Contour Feature**

Chun-Wen Hung, Chih-Li Huo, Yu-Hsiang Yu, Tsung-Ying Sun
National Dong Hwa University, Hualien, Taiwan, R.O.C.

17:20 – 17:40 **Applying Weighted Mean Aggregation to Edge Detection of Images**

Jyh-Yeong Chang, Yi-Hsin Chang
National Chiao Tung University, Hsinchu, Taiwan

16:00 – 17:40 [T2c] SESSION on Intelligent Control — Room F07

Session Chair: ***Shyh-Feng Chen***

16:00 – 16:20 **An Instrument-based Testing Platform and Fuel Control Algorithm Verification for Direct Methanol Fuel Cell**

Sheng-Hua Chen*, Ya-Chien Chung**, Tzyy-Yih Yang**, Yu-Jen Chiu**, Jin-Yih Lin**, Chen-Tung Chi**
* Ship and Ocean Industries R&D Center, New Taipei City, Taiwan
** Taipei Chengshih University of Science and Technology, Taipei City, Taiwan

16:20 – 16:40 **Control Theoretic Properties of Physiological Controller Motifs**

Kristian Thorsen, Peter Ruoff, Tormod Drengstig
University of Stavanger, Norway

16:40 – 17:00 **Tower Crane Sway Control with Inclinometer Feedback and Dual Loop Control Structure**

Chwan-Hsen Chen

Yuan Ze University, Chung Li City, Taiwan

17:00 – 17:20 **State Feedback Controller Design for Discrete-Time Singular Systems with Random Packet Losses**

Shyh-Feng Chen
China University of Science and Technology, Taipei, Taiwan, R.O.C.

17:20 – 17:40 **Novel Conditions for Finite Time Stability of Discrete Time Delay Systems**

D. Lj. Debeljkovic*, I. M. Buzurovic**, S. B. Stojanovic, A. M. Jovanovic****
* University of Belgrade, Belgrade, Serbia
** Harvard University, Boston, MA, USA
*** University of Nis, Leskovac, Serbia

16:00 – 17:40 [TP2] POSTER SESSION

Analysis of Synthetic Metabolic Pathways Solution Space

Jurijs Meitalovs, Egils Stalidzans
Latvia University of Agriculture, Latvia

Hybrid Multiple-Object Tracker Incorporating Particle Swarm Optimization and Particle Filter

Chen-Chien Hsu, Yung-Ching Chu
National Taiwan Normal University, Taipei, Taiwan

Ming-Chih Lu
St. John's University, Taipei, Taiwan

18:15 BUS DEPARTURE — from Óbuda University

19:00 – 22:00 BANQUET — Danube cruise

July 5, Friday

8:30 – 16:00 REGISTRATION

9:00 – 10:20 PARALLEL SESSIONS

9:00 – 10:20 [F1a] SESSION on Image Processing and Robot System II — Room F09

Session Chair: ***Wei-Yen Wang***

9:00 – 9:20 **Design and Implementation of Adaptive Dynamic Controllers for Wheeled Mobile Robots**

Yi-Feng Kao*, Yi-Hsing Chien*, I-Hsum Li**, Wei-Yen Wang*, Tsu-Tian Lee***
* National Taiwan Normal University, Taipei, Taiwan, R.O.C.
** Lee-Ming Institute of Technology, Taipei, Taiwan, R.O.C.
*** Chung Yuan Christian University, Taoyuan, Taiwan, R.O.C.

9:20 – 9:40 **Autonomous Stair Detection and Climbing Systems for a Tracked Robot**

Chien-Kai Tseng*, I-Hsum Li**, Yi-Hsing Chien*, Ming-Chang Chen, Wei-Yen Wang****
* National Taiwan Normal University, Taipei, Taiwan, R.O.C.
** Lee-Ming Institute of Technology, Taipei, Taiwan, R.O.C.
*** National Taiwan University of Science and Technology, Taipei, Taiwan, R.O.C.

9:40 – 10:00 **Image-based Obstacle Avoidance and Path-Planning System**

Yi-Han Chen*, Ming-Chang Chen**, I-Hsum Li, Wei-Yen Wang*, Shun-Feng Su*****
* National Taiwan Normal University, Taipei, Taiwan, R.O.C.
** National Taiwan University of Science and Technology, Taipei, Taiwan, R.O.C.
*** Lee-Ming Institute of Technology, Taipei, Taiwan, R.O.C.

10:00 – 10:20 **Educational Robots as Collaborative Learning Objects for Teaching Computer Science**

R. Burbaite, V. Stuikys, R. Damasevicius
Kaunas University of Technology, Kaunas, Lithuania

9:00 – 10:20 [F1b] SESSION on Intelligent Robot System Room F08

Session Chair: ***Ching-Chih Tsai***

9:00 – 9:20 **Target Object Announcement by Synchronous Blinking of a Robot and an Object**

Mitsuharu Matsumoto, Sayako Hata
The University of Electro-Communications, Japan

9:20 – 9:40 **Study on Constructing Forensic Procedure of Digital Evidence on Smart Handheld Device**

Chih-Pai Chang*, Chun-Te Chen*, Tsung-Hui Lu*, I-Long Lin**, Po Huang, Hua-Shyun Lu*****
* Huafan University, Taipei, R.O.C.
** Yuanpei University, HsinChu, R.O.C.
*** iForensics Digital Inc., Taipei, R.O.C
**** Kang-Ning Junior College of Medical Care and Management, Taipei City, R.O.C.

9:40 – 10:00 **Adaptive Robust Motion Control Using Fuzzy Wavelet Neural Networks for Uncertain Electric Two-Wheeled Robotic Vehicles**

Ching-Chih Tsai, Ching-Hang Tsai

10:00 – 10:20 **Design and Implementation of a 4WS4WD Mobile Robot and Its Control Applications**

Chih-Jui Lin, Su-Ming Hsiao, Ying-Hao Wang, Cheng-Hao Yeh, Chien-Feng Huang, Tzuu-Hseng S. Li
National Cheng Kung University, Tainan, Taiwan, ROC

9:00 – 10:20 [F1c] SESSION on Neural Networks Room F07

Session Chair: ***Michal Rojček***

9:00 – 9:20 **Classification of Slovak Municipalities by Neural Networks with Regard to the Degree of Digital Literacy Index**

Alžbeta Michalíková, Soňa Volentierová
Matej Bel University, Banská Bystrica, Slovakia

9:20 – 9:40 **Decentralized Adaptive Control Using an Affine plus Self-organizing Fuzzy Neural Network for Multi-Agent System Consensus Problem**

Masanao Obayashi*, Yasuhiro Otomi*, Takashi Kuremoto*, Kunikazu Kobayashi**, Shingo Mabu*
* Yamaguchi University, Ube, Yamaguchi, Japan
** Aichi Prefectural University, Nagakute, Aichi, Japan

9:40 – 10:00 **Clustering of Text Collections based on PART Neural Network and Similarity Measure**

R. Krakovsky* and I. Mokris**
* Catholic University, Ruzomberok, Slovakia
** Institute of Informatics, Slovak Academy of Sciences, Bratislava, Slovakia

10:00 – 10:20 **System for Document Clustering from mixed Sources based on Fuzzy ART Neural Network**

Michal Rojček*, Igor Mokriš**
* Catholic University in Ružomberok, Ružomberok, Slovakia
** Institute of Informatics, Slovak Academy of Sciences, Bratislava, Slovakia

9:00 – 10:20 [FP1] POSTER SESSION

Robust Tracking Controller Design and Its Application to Wheeled Robot

Kuo-Ho Su*, Minh-Hoang To*, Chan-Yun Yang**
* Chinese Culture University, Taipei, Taiwan
** National Taipei University, New Taipei City, Taiwan

A Computer Vision System for Fast AR Film Thickness Measurement of Polysilicon Solar Cells

Hsu-Nan Yen*, Hsi-Ting Hou**

* St. John's University, New Taipei City, Taiwan, R.O.C.
** Tamkang University, New Taipei City, Taiwan, R.O.C.

10:20 – 10:40 COFFEE BREAK

10:40 – 12:00 PARALLEL SESSIONS

10:40 – 12:00 [F2a] SESSION on Machine Vision and Map Building — Room F09

Session Chair: ***Chen-Chien Hsu***

10:40 – 11:00 **Machine-Vision-based Obstacle Avoidance System for Robot System**

Cheng-Pei Tsai*, Chin-Tun Chuang**, Ming-Chih Lu**, Wei-Yen Wang, Shun-Feng Su*, Shyang-Lih Chang****

* NTUST, Taipei City, Taiwan
** St. John's University, New Taipei City, Taiwan
*** NTNU, Taipei City, Taiwan

11:00 – 11:20 **Map Building of Unknown Environment Using PSO-tuned Enhanced Iterative Closest Point Algorithm**

Chen-Chien Hsu, Hua-En Chang

National Taiwan Normal University, Taipei, Taiwan

Yin-Yu Lu

University of Melbourne, Melbourne, Australia

11:20 – 11:40 **High Speed Gaze Tracking with Visible Light**

Wen-Chung Kao, Wei-Te Chang, Sheng-Ju Wu, Chien-Hui Liu, Shih-Yao Yin

National Taiwan Normal University, Taipei, Taiwan

11:40 – 12:00 **Time Sequence-based Lane-Marking Identification**

Jiun-Hung Li, Chih-Li Huo, Yu-Hsiang Yu, Tsung-Ying Sun

National Dong Hwa University, Hualien, Taiwan, R.O.C

10:40 – 11:40 [F2b] SESSION on Intelligent Data Analysis and Applications — Room F08

Session Chair: ***Kao-Shing Hwang***

10:40 – 11:00 **Reinforcement Learning with Model Sharing for Multi-Agent Systems**

Kao-Shing Hwang*, Wei-Cheng Jiang**, Yu-Jen Chen**, Wei-Han Wang**

* National Sun Yat-sen University, Kaohsiung, Taiwan, R.O.C.
** National Chung Cheng University, Chiayi, Taiwan, R.O.C.
*** Precision Machinery Research & Development Center, Taichung, Taiwan, R.O.C.

11:00 – 11:20 **Possibilistic *c*-Regression Models Clustering Algorithm**

Chung-Chun Kung*, Hong-Chi Ku* and Jui-Yiao Su*

* Tatung University, Taipei, Taiwan, R.O.C.
* Industrial Technology Research Institute (ITRI), Hsinchu, Taiwan, R.O.C.

11:20 – 11:40 **Modelling and Analysing Defence-in-Depth in Arming Systems**

Dan Slipper and Alistair A. McEwan

University of Leicester, Leicester, UK

Wilson Ifill

AWE Aldermaston, Berkshire, UK

10:40 – 11:40 [F2c] SPECIAL SESSION on Emerging PhD Research in Applied System Science and Informatics — Room F07

The session was organized by the Doctoral School of Applied Informatics, Óbuda University, Budapest, Hungary

Session Chair: ***László Horváth***

10:40 – 11:10 **About Performance Requirements Set against Consumer-Grade Geolocation Technologies**

Ferenc Brachmann
University of Pécs, Pécs, Hungary

11:00 – 11:20 **Quantum Structure Classification by Kohonen Self-Organizing Map and by Fuzzy C-Means Algorithm**

Antal Ürmös*, Márk Farkas**, László T. Kóczy, Ákos Nemcsics****
* Óbuda University, Budapest, Hungary
** Nexogen Ltd., Budapest, Hungary
*** Széchenyi István University, Győr, Hungary

11:20 – 11:40 **PID Controller Parameter Estimator Using Ant Colony System**

Hung-Ching Lu*, Hsi-Kuang Liu**, Lian-Fue Yang**
*,** Tatung University, Tatung University, Taipei, Taiwan
,* Taipei College of Maritime Technology, Taipei, Taiwan

10:40 – 12:00 [FP2] POSTER SESSION

Monitoring of Processes in Component Joints by Intelligent System

Zuzana Murčinková*, Jaromír Murčinko*
* Technical University in Košice with seat in Prešov, Slovak Republic
** DELTA FIT, Slovak Republic

12:00 – 13:20 LUNCH

13:20 – 15:20 PARALLEL SESSIONS

13:20 – 15:20 [F3a] SESSION on Intelligent Systems and Applications I — Room F09

Session Chair: ***Germano Resconi***

13:20 – 13:40 **Mobile Performance Metrics for Resource Management**

Krisztián Pándi, Hassan Charaf
Budapest University of Technology and Economics, Budapest, Hungary

13:40 – 14:00 **The Solution Area-based Approach of the Content-Driven Template-Based Layout System**

István Albert, Sándor Kolumbán, Hassan Charaf, László Lengyel
Budapest University of Technology and Economics, Budapest, Hungary

14:00 – 14:20 **Inside the Ticketing System and the Benefits Brought by It**

Patrick Stefanescu, Marian Mocan, Werner Stefanescu
University "Politehnica" of Timişoara, Timişoara, Romania

14:20 – 14:40 **Condition Monitoring of Transformer Bushings Using Rough Sets, Principal Component Analysis and Granular Computation as Preprocessors**

JT Maumela*, FV Nelwamondo*#, T Marwala*
* University of Johannesburg, Auckland Park, South Africa
# Council of Scientific and Industrial Research, Pretoria, South Africa

14:40 – 15:00 **Model Choice for Binned-EM Algorithms of Fourteen Parsimonious Gaussian Mixture Models by BIC and ICL Criteria**

Jingwen Wu, Hani Hamdan
SUPELEC, France

15:00 – 15:20 **Morphogenetic Evolution**

Germano Resconi
Catholic University, Brescia, Italy

13:20 – 15:20 [F3b] SESSION on System of Systems — Room F08

Session Chair: ***Gyula Hermann***

13:20 – 13:40 **Systems of Systems Engineering: A Research Imperative**

Michael Henshaw, Carys Siemieniuch*, Murray Sinclair*, Sharon Henson*, Vishal Barot*, Mo Jamshidi**, Dan Delaurentis***, Cornelius Ncube****, Soo Ling Lim****, and Huseyin Dogan*****
* Loughborough University, Loughborough, UK
** University of Texas, San Antonio, US
*** Purdue University, West Lafayette, US
**** Bournemouth University, Dorset, UK

13:40 – 14:00 **The Implementation of ASG and SG Random Number Generators**

Esra Erkek, Taner Tuncer
Firat University, Elazig, Turkey

14:00 – 14:20 **A Novel Algorithm for Flattening Virtual Subsystems in Simulink Models**

Péter Fehér, Tamás Mészáros and László Lengyel
Budapest University of Technology and Economics, Budapest, Hungary

Pieter J. Mosterman
Research and Development, MathWorks, Natick, MA, USA

14:20 – 14:40 **Stabilizing Switching Laws for Switched LPV Systems with All Unstable Subsystems**

Xu He, Gyorgyi Dymirkovsky***
* Chinese Academy of Sciences, Shenyang, Liaoning, P.R. China
** Dogus University, Istanbul, R. Turkey

14:40 – 15:00 **LPV Systems with Unstable Subsystems: A Single Lyapunov Function Solution to Stabilizing Switching Laws**

Xu He, Gyorgyi Dymirkovsky***
* Chinese Academy of Sciences, Shenyang, Liaoning, P.R. China
** Dogus University, Istanbul, R. Turkey

15:00 – 15:20 **Reengineering Urban Metabolism: Simulation and Control of Allied Biomakeries**

István Kenyeres
BIOPOLUS Institute, Budapest, Hungary

13:20 – 15:20 [FP3] POSTER SESSION

Binary Decision Diagram Optimization Method Based on Multiplexer Reduction Methods

Marián Maruniak, Peter Pištek
Slovak University of Technology in Bratislava, Bratislava, Slovakia

15:20 – 15:40 COFFEE BREAK

15:40 – 17:20 PARALLEL SESSIONS

15:40 – 17:20 [F4a] SESSION on Intelligent Systems and Applications II — Room F09

Session Chair: ***Tsung-Ying Sun***

15:40 – 16:00 **Study on Constructing Malware Attack Forensic Procedure of Digital Evidence**

Chih-Pai Chang*, Chun-Te Chen*, Tsung-Hui Lu*, I-Long Lin**, Jesse Chang, Chen-Cheng Lin****
* Huafan University, Taipei, R.O.C.
** Yuanpei University, HsinChu, R.O.C.
*** Acro Technology Company, Taipei, R.O.C

16:00 – 16:20 **An Effective Teeth Segmentation Method for Dental Periapical Radiographs Based on Local Singularity**

P. L. Lin*, P. Y. Huang**, P. W. Huang*
* Providence University, Shalu, Taichung, Taiwan
** National Chung Hsing University, Taichung, Taiwan

16:20 – 16:40 **A Novel Calibration Method based on Heuristic B-spline Model for Fish-Eye Lenses**

Jie-Shou Lu, Chih-Li Huo, Yu-Hsiang Yu, Tsung-Ying Sun
National Dong Hwa University, Hualien, Taiwan

16:40 – 17:00 **A Case Study on Privacy Information Protection in Campus**

Tsung-Hui Lu, Zne-Jung Lee
Huafan University, New Taipei City, Taiwan

17:00 – 17:20 **Applying Rough Set Theory to Establish the Knowledge Base of Ammunition Management**

Hua-Kai Chiou*, Yong-Ting Huang**, Mei-Chun Mao*
* China University of Science and Technology, Taipei, Taiwan
** National Defense University, Taipei, Taiwan

15:40 – 17:20 [F4b] SESSION on Intelligent Power and Energy Systems — Room F08

Session Chair: ***Yao-Ching Hsieh***

15:40 – 16:00 **Methods to Compare Coalition's Prevention Power Derived from Effectivity for Social Choice Correspondence**

Kentaro Kojima
Aoyama Gakuin University, Kanagawa, Japan

16:00 – 16:20 **Global Efficiency of an UPS Module Integrated with PV, H2, and CAES Systems**

Nicola Pio Belfiore, Matteo Verotti, Silvia Sangiorgio and Luca Rubini
Sapienza University of Rome, Rome, Italy

16:20 – 16:40 **Battery Power System with Arrayed Battery Power Modules**

Chin-Sien Moo*, Jhen-Yu Jian*, Tsung-Hsi Wu*, Li-Ren Yu*, Chih-Chiang Hua*
* National Sun Yat-sen University, Kaohsiung, Taiwan
** National Yunlin University of Science & Technology, Yunlin, Taiwan

16:40 – 17:00 **Operation of Battery Power Modules with Bidirectional DC/DC Converters**

Tsung-Hsi Wu*, Chin-Sien Moo*, Yao-Ching Hsieh**, and Chun-Ying Juan**
* National Sun Yat-sen University, Kaohsiung City, Taiwan
** National Dong Hwa University, Hualien City, Taiwan
*** MIRDC Metal Industries, Taipei City, Taiwan

17:00 – 17:20 **Balanced Discharging for Serial Battery Power Modules with Boost Converters**

Li-Ren Yu*, Yao-Ching Hsieh**, Wei-Chen Liu*, Chin-Sien Moo*
* National Sun Yat-sen University, Kaohsiung City, Taiwan
** National Dong Hwa University, Hualien City, Taiwan

15:40 – 17:20 [FP4] POSTER SESSION

Analysis and Design of a Single-Switch HPF AC/DC Converter for Driving Power LEDs

Hung-Liang Cheng*, Yong-Nong Chang**, Chun-An Cheng* and Chao-Shun Chen*
* I-Shou University, Kaohsiung, Taiwan, R.O.C.

** National Formosa University, Yunlin County, Taiwan, R.O.C.

17:20 **Closing Ceremony and Invitation to ICSSE 2014** **Room F09**

18:00 **Gala Dinner ______________________** **NIK Aula**

Same building, wing 'NIK', first floor

Admissibility of Fuzzy Support Vector Machine through Loss Function

Chan-Yun Yang*, Gene Eu Jan**, Kuo-Ho Su***

*, ** National Taipei University/Department of Electrical Engineering, New Taipei City, Taiwan

*** Chinese Culture University/Graduate Institute of Digital Mechatronic Technology, Taipei, Taiwan

cyyang@mail.ntpu.edu.tw; gejan@mail.ntpu.edu.tw; sgh@faculty.pccu.edu.tw

***Abstract*—In statistical decision theory, the admissibility is the first issue to fulfill the feasibility of a decision rule. Without the admissibility, the decision rule is impractical for discriminations. The study decomposes first the fuzzy support vector machine (fuzzy SVM), which is a crucial innovation due to its robust capability to resist the input contaminated noise, into a regularized optimization expression *arg* $\min_{f\in H}$ $\Omega[f]+\lambda_R R_{\mathrm{emp}}[f]$ and exploits the regularization of loss function from the expression mathematically. The decomposition is beneficial to the programming of empirical risk minimization which uses the empirical risk instead of the true expected risk to learn a hypothesis. The empirical risk, composed elementally by the loss function, here indeed is the key for achieving the success of the fuzzy SVM. Because of the important causality, the study examines preliminarily the admissibility of loss functions which is recruited to form the fuzzy SVM. The examination is issued first by a loss function associated risk, called □-risk. By a step-by-step derivation of a sufficient and necessary condition for the □-risk to agree equivalently an unbiased Bayes risk, the admissibility of the loss function can then be confirmed and abbreviated as a simple rule in the study. Experimental chart examination is also issued simultaneously for an easy and clear observation to validate the admissibility of the loss function regularized fuzzy SVM.**

Index Terms*: Robust, Fuzzy, Support Vector Machine, Loss Function, Admissibility.*

I. REGULARIZATION AND LOSS FUNCTION

From the viewpoint of optimization, a generalized statistical learning classifier, including support vector machine (SVM) and boosting, can in general be expressed as a regularization form [1–3]:

$$\arg\min_{f\in F\in H} \lambda_\Omega \Omega[f]+R_{\mathrm{emp}}[f], \tag{1}$$

where $\Omega[f]$ is a regularization term, and $R_{\mathrm{emp}}[f]$ is a term of empirical risk acquired from a set of finite training samples [4–5]. The regularized model seeks a hypothesis f in a hypothesis set F by optimizing simultaneously both the empirical risk and the regularization term with a ratio constant, termed as a regularization factor, λ_Ω. In the expression, H represents a high dimensional Reproducing kernel Hilbert feature space (RKHS) [6] mapped from a low dimensional input space by a kernel function for solving non-linearly a complex classification.

The study first aims to discover admissibility of loss functions which are used in this type of regularization. For convenience of the discovery, we move thus the regularization factor to the other term in the binominal objective function, and rewrites the expression in (1) as:

$$\arg\min_{f\in F\in H} \Omega[f]+\lambda_R R_{\mathrm{emp}}[f], \tag{2}$$

where λ_R is also a regularization factor to control the trade-off between the classifier complexity and misclassification loss during the training. In SVM, we facilitate $\Omega[f]$ = $1/2\|\mathbf{w}\|^2$ to achieve the classification the maximal margin in the feature space, and represent the objective function as:

$$\arg\min_{f\in F\in H} \frac{1}{2}\|\mathbf{w}\|^2+\lambda_R R_{\mathrm{emp}}[f]\cdot \tag{3}$$

As the finite training samples we merely had in a machine learning practical, we did not know in advance the whole fact of sample distribution from the finite samples. That is said, in general, that merely those known samples were taken instead for designing the classifier, i.e., the empirical risk $R_{\mathrm{emp}}[f]$ was used instead the expected risk $R[f]$ in an actual classifier design. In fact, the alternated empirical risk is irresolute due to it may cause unsatisfactorily an underfitting or overfitting of the learned hypothesis if the decision rule is inadmissible. To prevent from the irresolution and ensure the existence of an exact fitted solution, one learning consistency theorem is issued by Vapnik [4–5]. The issued consistency promises that the optimal empirical risk would converge asymptotically to the real expected risk if the sample size was sufficiently large (Fig. 1). The asymptotic consistency which is admitted elementally to Fisher consistency [7] is a crucial fundamental to guarantee the feasibility of a statistical learning machine, certainly including SVM. By extending the asymptotic consistency, we can guarantee a solution sufficiently close to the optimal solution obtained from the real expected risk by using merely the finite samples if the samples size is sufficiently large.

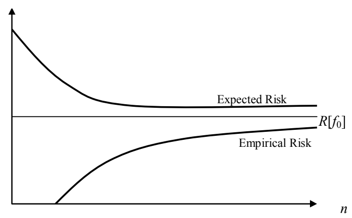

Figure 1. Asymptotic consistency in both empirical risk and expected risk when the sample size approaching to infinity

Relevant to the topic of regularization, we begin with a set of n learning samples, $S=\{(\mathbf{x}_i, y_i)\}\in(X\times Y)^d$, $i=1,2,\ldots,n$, where $\mathbf{x}_i=[\mathbf{x}_i^1, \mathbf{x}_i^2, \ldots, \mathbf{x}_i^d]\in X\in R^d$ is an input training sample, $y_i=\{-1, 1\}\in Y$ is its corresponding actual output, and define first the expected risk as:

$$R[f]=\int_{X\times Y} R_\phi(y,f(\mathbf{x}))dp(\mathbf{x},y), \tag{4}$$

where $p(\mathbf{x},y)$ denotes the probability of learning sample $\mathbf{x}$ having class label y. Related to the definition, the empirical risk is given as:

$$R_{\mathrm{emp}}[f]=\frac{1}{n}\sum_{i=1}^{n} R_\phi(y_i,f(\mathbf{x}_i))\cdot \tag{5}$$

As an estimation of the real expectation of risk $R[f]$, the empirical risk $R_{\mathrm{emp}}[f]$ is often employed in empirical risk minimization (ERM) [4–5] for pursuing the best hypothesis f in the functional set F. Together with simultaneously minimizing the regularization term, ERM can be extended to the so called structural risk minimization (SRM) for following the pursue much structural in the functional set F [4]. As it in (5), a loss function $\phi(y_i, f(\mathbf{x}_i))$ is introduced to evaluate and respond the prediction error to adapt the empirical risk for learning the hypothesis f. The loss function is an important surrogate to convert training errors and is used to directly reflect the significance of the errors for assessing the hypothesis f. To clarify the loss function, we assume an arbitrary sample i with $\mathbf{x}_i\in X$, $y_i\in Y$, and its predicted value $f(\mathbf{x}_i)$ has a loss function map $\phi(y_i, f(\mathbf{x}_i))\in X\times Y$ such that ϕ: $X\times Y\rightarrow[0, \infty]$. With the definition, a misclassified sample is generally assigned with a nonzero loss function value. The more serious the misclassification is, the higher the loss function value is assigned, and a zero loss function value is assigned for an exact prediction, i.e., $\phi(y_i, y_i) = 0$. As expressed in (5), the empirical risk in fact is a mean value of all the loss function values of the n training samples. To adapt the minimal error in ERM, such as the minimization in (2), the loss function is used as a metric to penalize the misclassified sample. The scale of the penalty depends on the difference between actual output and its corresponding predicted value. Using the penalty, one can force the optimizer to reduce the misclassifications, not only the individual misclassified level but also the total misclassification counts. Figure 2 showed different kinds of loss function for regularized classification [8]. In the figure, the metric $y_if(\mathbf{x}_i)$ marked in the horizontal axis was the so called margin. It is the reason that these kinds of $\phi(y_i, f(\mathbf{x}_i))$ have been categorized as margin-based loss functions [9]. Zhang gave their explicit mathematical forms as follows [10]:

a. 0-1 misclassification loss function:
$$\phi(y_if(\mathbf{x}_i))=\max(sign(-y_if(\mathbf{x}_i)),0)\ ,$$
b. Squared error loss function:
$$\phi(y_if(\mathbf{x}_i))=(1-y_if(\mathbf{x}_i))^2,$$
c. Modified squared error loss function:
$$\phi(y_if(\mathbf{x}_i))=\max(1-y_if(\mathbf{x}_i),0)^2,$$
d. Hinge loss function:
$$\phi(y_if(\mathbf{x}_i))=\max(1-y_if(\mathbf{x}_i),0)\ ,$$
e. Exponential loss function:
$$\phi(y_if(\mathbf{x}_i))=\exp(-y_if(\mathbf{x}_i))\ \text{, and}$$
f. Logistic regression loss function:
$$\phi(y_if(\mathbf{x}_i))=\ln(1+\exp(-y_if(\mathbf{x}_i)))\ \cdot$$

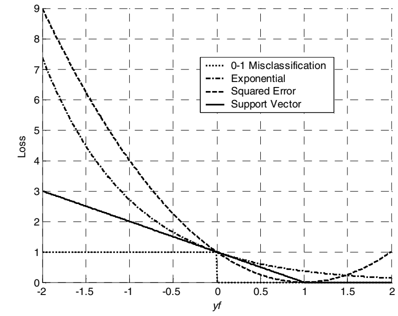

Figure 2. Types of loss function for regularization

Lugosi and Vayatis [11] have proposed that a monotonic, differentiable, and strictly convex loss function ϕ for statistical learning classification, with $\phi(0)=1$, would consistently converge its generalized risk to the Bayes risk under an adequate regularization.

II. SURROGATE LOSS FUNTION IN FUZZY SVM

Fuzzy support vector machines arose due to difficulties in unambiguously producing a generalized separating hyperplane with undesired uncertainty incurred by some contaminated noisy samples. Fuzzy numbers, $0 \le s_i \le 1$, $i = 1, 2, ..., n$, for carrying additional information to reflect the contaminated noisy level of the samples are hence introduced, and change S as $S = \{(\mathbf{x}_i, y_i, s_i)\}$, $i = 1, 2, \ldots, n$. At the beginning, researchers, including Lin and Wang [12], Huang and Liu [13], Chu and Wu [14], and Tao and Wang [15] were inspired by introducing the fuzzy numbers to reduce the influence of the contaminated noisy samples in the SVM training, and developed different kinds of fuzzy support vector machines. As the unsophisticatedness, the model from Lin and Wang [16] is an elegant one among the developments, and has been hired in many applications. For the other variants, Wu and Srihari [17] proposed a weighted margin SVM to join the prior knowledge in the training samples, and realized the sequential minimal optimization (SMO) was still practicable in the proposed algorithm, and Yang et al., [18] tied straightforward the fuzzy numbers to the class labels to develop a more interested model which had equivalent generalization capability. Ma and Kong [19] and Lin and Wang [20] extended later the theory and contributed to kind of applications. Several relevant topics are also discussed by Mill and Inoue [21], Tsujinishi and Abe [22], Zheng and Zheng [23]. In general, the use of a fuzzy support vector machine is more resistant to the sample noise, and conducts a better robustness of the classifier to the noise.

In fact, the sustainability of the robustness can be significantly abstracted as an introducing s_i to the loss function [24]. It is no wonder that the loss function is the key to decision rule for learning with SVM. The study uses the hinge loss function, which is first created by Cortes and Vapnik [4], for inspecting the effects caused by s_i introduction, and hence does the admissibility analysis. Due to the introduction, the hinge loss function becomes:

$$\xi_i = \phi(y_i f(\mathbf{x}_i)) = \max s_i (1 - y_i f(\mathbf{x}_i), 0) \ , \tag{6}$$

where slack variable ξ_i, i=1,2,…,n, acquire the loss function values of every sample i , and form subsequently a vector $\boldsymbol{\xi} = [\xi_1, \xi_2, ..., \xi_n]^{\mathrm{T}}$ for fuzzification. With ξ_i, the primal problem of the fuzzy SVM is given as [16]:

$$\arg\min_{\mathbf{w},\xi} \frac{1}{2}\|\mathbf{w}\|_2^2 + C\sum_{i=1}^{n} s_i \xi_i \ ,$$

subject to (7)

$$y_i (k(\mathbf{w}, \mathbf{x}_i) + b) \geq 1 - \xi_i \ .$$

The objective function and constraints of corresponding dual problem are thus written as:

$$\arg\max_{\boldsymbol{\alpha}} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j k(\mathbf{x}_i, \mathbf{x}_j) \ ,$$

subject to (8)

$$0 \leq \alpha_i \leq s_i C \ , \text{ and } \sum_{i=1}^{n} \alpha_i y_i = 0 \ , \ \forall i \ .$$

By solving the quadratic optimization dual problem with respect to the Lagrange multipliers $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, ..., \alpha_n]^{\mathrm{T}}$, we can eventually obtained the decision function:

$$f(\mathbf{x}) = \sum_{i=1}^{n} y_i \alpha_i k(\mathbf{x}_i, \mathbf{x}) + b \ . \tag{9}$$

Referring to the standard SVM (s_i = 1) [4], a family of loss functions of fuzzy SVM with different s_i is depicted in Figure 3, and can summarily be characterized as:

a. All the loss functions come with a identical hinge point at $y_i f(\mathbf{x}_i) = 1$. At this point, $\phi(1) = 0$. A margin $y_i f(\mathbf{x}_i)$ higher than 1 would conduct a zero loss function value.

b. The slope of nonzero part of the loss function is controlled by s_i. As larger s_i, the steeper slope it would be.

c. The value of s_i scales only up or down the applied penalty in the optimization with a fixed margin, i.e., the regularization of s_i only takes effect on the penalty. No effect is taken on the margin.

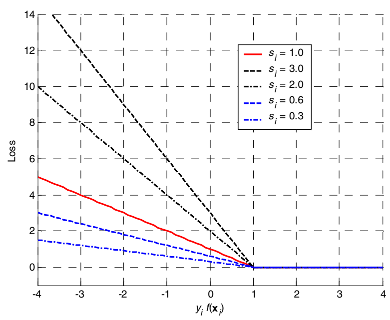

Figure 3. Loss functions of fuzzy SVM with different s_i

III. METHOD FOR ADMISSIBILITY EXAMINATION

Our mission in this study is to examine the admissibility of the loss function $\phi(y_i f(\mathbf{x}_i))$. As its importance for the asymptotic consistency, the loss function has first to be admissible to the decision rule, and then achieve sufficiently the monotonic, differentiable, and strictly convex conditions [9–10, 25–26]. The definition of admissibility is thus given as below.

Theorem 1 (Stein, 1955 [27]). In statistical decision theory, a decision function f is inadmissible if there exists a different decision function f' such that $R(f', \theta) \leqq R(f, \theta)$ for all θ with a strict inequality $R(f', \theta) < R(f, \theta)$ for some θ, where θ belongs to the distribution of states of nature Θ. A decision function f is admissible if it is not inadmissible. ¶

Consulting Stein [27], we can prove Theorem 1. Bartlett also classified the loss functions which are admissible as which classification calibrated [26]. The theorem implies that an admissible decision function is a hypothesis for making a decision such that no any other hypothesis can always be better than it [28–29].

For a loss function ϕ, we check the Bayes theory and redefine the Bayes risk with respect to ϕ.

Definition 1. For a given prior distribution Θ, a risk of decision hypothesis f with respect to a loss function ϕ satisfying:

$$R_\phi(f^*, \Theta) = \inf_{f \in F} R_\phi(f, \Theta) \tag{10}$$

is the Bayes risk of f. ¶

Theorem 2 (James and Stein, 1961 [30]). Any Bayes decision hypothesis f^* with respect to loss function ϕ is admissible. ¶

Proof. Suppose f^* is the unique Bayes classifier with respect to the given loss function ϕ and is inadmissible. There hence exists a particular hypothesis f such that $R(f, \theta) \leqq R(f^*, \theta)$ for all θ and $R(f, \theta) < R(f^*, \theta)$ for some θ, and thus

$$\int_\Theta R_\phi(f, \theta) dp(\theta) \leq \int_\Theta R_\phi(f^*, \theta) dp(\theta) \ , \tag{11}$$

which obviously disagrees with the uniqueness of f^* with respect to □, and hence f^* is admissible.

To show the asymptotic consistency of a loss function regularized SVM, a condition for Bayes risk below hence must be fulfilled for an equivalence to the real Bayes risk:

Theorem 3. A regularized loss function ϕ in a SVM is admissible if and only if

$$\inf_{f \in F} R_\phi(f, \Theta) = R_\phi^* \Rightarrow \inf_f R(f, \Theta) = R^* \ , \tag{12}$$

where $R(f, \Theta)$ denotes the risk of hypothesis f undertook with prior Θ, $R_\phi(f, \Theta)$ denotes the undertaken risk with respect to the loss function ϕ, and R^* denotes the unique standard Bayes risk. ¶

Theorem 3 can be proved by consulting Steinwart's [25] and Bartlett's [26] works. The theorem assesses that the undertaken risk tends towards the unique standard Bayes risk if the risk taken by a ϕ regularized SVM tends towards its minimal values, and guarantees that the minimal ϕ-risk is potentially a candidate for the admissibility analysis. Considering further Theorem 2, the analysis can thus be narrowed down and realized by an examination of R_ϕ^*. Under the condition when R□ reaching the optimal R_ϕ^*, if the corresponding f_ϕ^* is capable to achieve an unbiased estimation, an admissible f can hence straightforward be asserted. With this regard, Bartlett [26] has employed the definition of expected risk $R(f)$ to clarify the relationship between the expected risk of f with respect to ϕ and the hypothesis f, and define a ϕ-risk as:

$$R_\phi(f) = \mathbf{E}_{X,Y}[R_\phi(yf(\mathbf{x}))] \cdot \tag{13}$$

According to the binomial theorem, the ϕ-risk of f can be decomposed into two parts due to the binary classification. One is the risk to label sample $\mathbf{x}$ as +1 and the other as –1. To take account the prior over the whole distribution, we have to consider more the probabilities of the class labels. By the probability η for labeling $\mathbf{x}$ as +1, $\eta \in [0, 1]$, the decomposed ϕ-risk is given as:

$$\mathbf{E}_{X,Y}[\phi(yf(\mathbf{x}))] = \mathbf{E}_X[\eta(\mathbf{x})\phi(f(\mathbf{x})) + (1-\eta(\mathbf{x}))\phi(-f(\mathbf{x}))] \cdot \tag{14}$$

To suppress the dependence of the analysis on Y, we consider only the fixed +1 labeled samples for the analysis, and represent a conditional ϕ-risk as below for the specified conditional probability $\eta(x) = p(y = 1 | \mathbf{x} = x)$ with respect to $\mathbf{x} = x$:

$$\mathbf{E}_X[\phi(yf(\mathbf{x})) \mid \mathbf{x} = x] = \eta(x)\phi(f(x)) + (1-\eta(x))\phi(-f(x)) \cdot \tag{15}$$

With the specified $y = 1$ and $\mathbf{x} = x$, a simplified version of generic conditional ϕ-risk [10, 26], analog to the Bayes binomial risk, is abbreviated as:

$$R_\phi(f,\eta) = \eta\phi(f) + (1-\eta)\phi(-f), \tag{16}$$

and terms its infimum as an optimal ϕ-risk $R_\phi^*(\eta)$:

$$R_\phi^*(\eta) = \inf_{f \in F} R_\phi(f,\eta) = R_\phi(f_\phi^*(\eta),\eta), \tag{17}$$

that is, we can find a hypothesis f_i from the function set $F = \{f_1, f_2, \ldots f_i, \ldots\}$ to achieve the minimal $R_\phi^*(\eta)$:

$$\lim_{i\to\infty} Q(f_i,\eta) = \lim_{i\to\infty}(\eta\phi(f_i) + (1-\eta)\phi(-f_i)) = R_\phi^*(\eta) \cdot \tag{18}$$

Following R_ϕ^*, we have

$$f_\phi^* = \arg\min_{f \in F} R_\phi^*(f,\eta) \cdot \tag{19}$$

Based on the firm foundations of unbiased estimation of Bayes estimator in Theorem 3, the expressions (18)–(19) is easier for the admissibility analysis by checking behaviors of f_ϕ^* and R_ϕ^*. If both their behaviors are compatible with the standard unbiased Bayes risk, we then assert the loss function □ is admissible, and otherwise inadmissible. Frankly speaking, a loss function ϕ regularized decision hypothesis f is admissible if and only if the following conditions can be established. For a given $\eta \in [0, 1]$, the optimized $f_\phi^*(\eta)$ reaching the ϕ-risk $R_\phi(f, \eta)$ at the optimal $R_\phi^*(\eta)$ achieves an unbiased prediction $f_\phi^*(\eta) < 0$ if $\eta < 1/2$ and $f_\phi^*(\eta) > 0$ if $\eta > 1/2$ like the true Bayes estimator. With the expressions (18)–(19), Zhang [10] derived the $f_\phi^*(\eta)$ and $R_\phi^*(\eta)$ for some known loss functions as follows for better admissibility examination:

a. Least squares loss function:
$f_\phi^*(\eta) = 2\eta - 1$, $R_\phi^*(\eta) = 4\eta(1-\eta)$,

b. Modified least squares loss function:
$f_\phi^*(\eta) = 2\eta - 1$, $R_\phi^*(\eta) = 2\eta - 1$,

c. Hinge loss function:
$f_\phi^*(\eta) = sign(2\eta - 1)$, $R_\phi^*(\eta) = 1 - |2\eta - 1|$,

d. Exponential loss function:
$f_\phi^*(\eta) = 1/2\ln(\eta/1-\eta)$,
$R_\phi^*(\eta) = 2\sqrt{\eta(1-\eta)}$, and

e. Logistic regression loss function:
$f_\phi^*(\eta) = \ln(\eta/1-\eta)$,
$R_\phi^*(\eta) = -\eta\ln\eta - (1-\eta)\ln(1-\eta)$.

IV. Results of Admissibility Examination

As it stood for in (6), the crucial loss function □ of fuzzy SVM, herein, must be examined for the adequate admissibility. For simplicity, the loss function is abbreviated by assigning $\eta(x) = p(y = 1 | \mathbf{x} = x)$ and a constant s for s_i as:

$$\phi(f) = \max s(1-f, 0) = \begin{cases} 0, & if\ f \geq 1 \\ s(1-f), & otherwise. \end{cases} \tag{20}$$

By substituting (20) into (16), the generic conditional ϕ-risk becomes:

$$R_\phi(f,\eta) = \begin{cases} s\eta(1-f), & \text{for } f \leq \text{-}1 \\ s(1 - f(2\eta - 1)), & \text{for } -1 < f < 1 \\ s(1-\eta)(1+f), & \text{for } f \geq 1. \end{cases} \tag{21}$$

By assuming $s > 0$, the $f_\phi^*(\eta)$ for achieving the minimal $R_\phi^*(f,\eta)$ is:

$$f_\phi^*(\eta) = \begin{cases} \text{-}1, & \text{for } f \leq \text{-}1 \\ sign(s(2\eta - 1)), & \text{for } -1 < f < 1 \\ 1, & \text{for } f \geq 1, \end{cases} \tag{22}$$

and we have eventually the $R_\phi^*(f,\eta)$ by substituting $f_\phi^*(\eta)$ into $R_\phi^*(f,\eta)$:

$$R_\phi^*(f,\eta)=\begin{cases} 2s\eta, & \text{for } f=-1 \\ s(1-|2\eta-1|), & \text{for } -1<f<1 \\ 2s(1-\eta), & \text{for } f=1 \end{cases} \qquad (23)$$

With the segmental definitions of $R_\phi(f, \eta)$, $f_\phi^*(\eta)$, and $R_\phi^*(f,\eta)$ in (21)–(23), plots of charting $R_\phi(f, \eta)$ with respect to f, and $f_\phi^*(\eta)$ and $R_\phi^*(f,\eta)$ with respect to η are issued for the examination (Figure 4). Two cases with s = 0.8, η = 0.6 and s = 0.3, η = 0.2 are depicted as those shown in the panels of the figure. By observing the panels, the minimal value of R□(f, η) falls consistently within the range of f = [–1, +1] with either η < 1/2 or η > 1/2 despite the different s settings. It is quite interesting that $f_\phi^*(\eta)$ maintains constantly at f = –1 or f = +1 for all $\eta \in$ [0, 1] and $\eta \neq$ 1/2; however the different s adoptions. It shows the excellent classification capability of the fuzzy SVM. The binomial expression of R□(f, η) ensures the symmetry for both of the charts of R□(f, η) as well as the optimized $R_\phi^*(f,\eta)$ to f = 0 and η = 1/2, respectively. By checking with Figure 4(b) and 4(d) and considering sign($f_\phi^*(\eta)$) = sign(s(2η–1)) in (22), it can be ensured that $f_\phi^*(\eta)$ < 0 if η < 1/2 and $f_\phi^*(\eta)$ > 0 if η > 1/2 under the optimal $R_\phi^*(f,\eta)$ has been reached for all $\eta \in$ [0, 1]. It guarantees the admissibility. In fact, the simultaneous symmetry of $R_\phi^*(f,\eta)$ also releases that $f_\phi^*(\eta)$ is capable of generate an even risk symmetric to the central η = 1/2, and confirms implicitly that $f_\phi^*(\eta)$ is an unbiased estimator.

V. Conclusion Remark

The study supports first a general method to examine the admissibility of the kind of loss function regularized hypotheses through the organized theorems, and develops extensively a generic conditional ϕ-risk specifically for fuzzy SVM admissibility. A chart examination is then facilitated to confirm the fact of the unbiased classification of the fuzzy SVM. Experiments shows a consistent result of the analysis.

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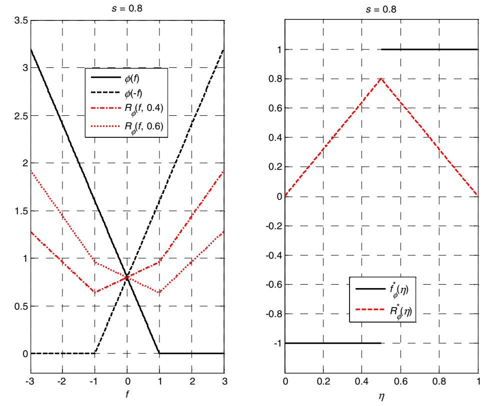
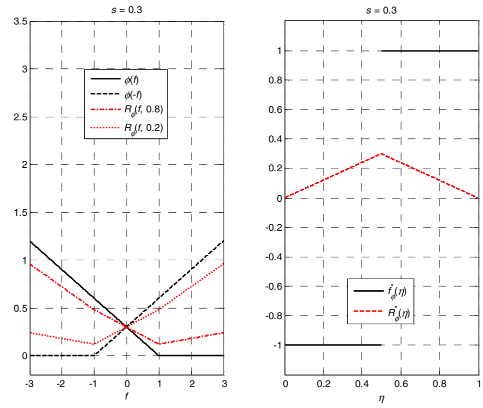


(a) $\phi(f)$ and R□(f, η) for η = 0.6 (b) $f_\phi^*(\eta)$ and $R_\phi^*(\eta)$



(c) $\phi(f)$ and R□(f, η) for η = 0.2 (d) $f_\phi^*(\eta)$ and $R_\phi^*(\eta)$

Figure 4. Loss function admissibility examination of fuzzy SVM. (a)-(b) setting s = 0.8, (c)-(d) setting s = 0.3

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Robust Tracking Controller Design and Its Application to Wheeled Robot

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Abstract— **A robust tracking controller is developed to improve the tracking performance for nonlinear dynamic system in this study. The proposed controller comprises a fuzzy PID sliding-mode controller (FPIDSMC) and an adaptive tuner. The FPIDSMC acts as the main tracking controller, which is designed via a fuzzy system to mimic the merits of a PID sliding-mode controller (PIDSMC). The adaptive tuner, which is derived in the sense of Lyapunov stability theorem, is utilized to adjust the parameter on-line for further assuring robust and optimal performance. In the FPIDSMC, the fuzzy rule base is compact and only one parameter needs to be adjusted. To verify its effectiveness and extend its application, the proposed adaptive fuzzy PID sliding-mode controller (AFPIDSMC) is applied to the path tracking of a wheeled robot, whose salient performance is verified by numerical simulation and whose advantages are presented in comparison with conventional AFSMC scheme under the same environment.**

I. INTRODUCTION

Many physical systems are nonlinear and dynamic. Due to the highly nonlinear and uncertain characteristics within them, it is difficult to evaluate the appropriate control effort to track the desired trajectory. To this end, much research has been done to apply various approaches, such as nonlinear state feedback technique, sliding-mode control (SMC), fuzzy control (FC), fuzzy neural network control (FNN), etc. Among these approaches, SMC is one of the effective nonlinear robust controllers since it provides system dynamics with an invariance property to uncertainties once the system dynamics are controlled in the sliding mode [1, 2]. However, the undesired chattering control effort might wear the mechanism and excite unstable system dynamics. On the other hand, FC has supplanted conventional technologies in many applications. One major feature of fuzzy system is its ability to express the amount of ambiguity in human thinking. Thus, when the mathematical model of the process does not exist, or exists but with uncertainties, FC is an alternative way to deal with the unknown process [3, 4]. However, the huge amount of fuzzy rules for high-order systems makes the analysis complex.

Therefore, much attention has focused on the fuzzy sliding-mode controllers (FSMC). However, the gradual increasing estimated upper bound, existed in some announced works, might induce the control effort into saturation and excite unstable system dynamics in some conditions [5, 6]. To improve this drawback, a PID sliding surface is adopted and incorporated into fuzzy inference engine to strengthen its anti-disturbance ability in this study. To further achieve satisfactory response, adaptive FC (AFC) and/or adaptive FSMC (AFSMC) schemes have been developed [7-9] for nonlinear dynamic system. With the dynamic adaptation mechanism, the parameters can be automatically adjusted. However, the number of parameters needed adjustment is generally deemed large such that the response time is lengthened. To improve this phenomenon, another objective of this study is to research a novel scheme which possesses compact fuzzy rule base and only one parameter needs to be adjusted.

Nowadays, the wheeled robot has been finding wide application in industrial, commercial and residential environments; however, the accurate model of the dynamic motion equation is difficult to establish or identify for designing an optimal path tracking controller. Also, the path tracking performance of a wheeled robot is influenced by system uncertainties, such as mechanical parameter variation, steering environment, payload changes, unstructured uncertainty due to nonideal motor control in transient state, unmodelled dynamics, etc. In recent years, the AFSMCs have been adopted to steer the wheeled robot path [10-15]. However, if the plant knowledge or control information is incomplete seriously then the load of adaptive algorithm will be heavy, the response time will be lengthened and the tracking error will be large. To verify the effectiveness of the proposed control scheme, the AFPIDSMC is applied to the path tracking of a wheeled robot. The design procedures and theoretical analyses of the proposed control system are described in detail. To compare with other AFSMC scheme [15], the same steering environment is employed in the simulation. The results are provided to demonstrate the effectiveness of the proposed AFPIDSMC tracking system and its advantages.

II. TRACKING CONTROLLER DESIGN FOR NONLINEAR DYNAMIC SYSTEM

A. Description of NonlinearDynamic Ssystem

Consider the nth–order nonlinear dynamic system of the form:

$$\begin{aligned} x^{(n)} &= f(\underline{x}) + g(\underline{x})u + d(t) \\ y &= x \end{aligned} \tag{1}$$

where $f(\underline{x})$ and $g(\underline{x})$ are unknown continuous functions, $g(\underline{x})$ is invertible; $u \in R$ and $y \in R$ are the control effort and output of the system, respectively; $\underline{x} = (x_1, x_2, \cdots, x_n)^T = (x, \dot{x}, \cdots, x^{(n-1)})^T \in \Re^n$ is the state vector of the system, which is assumed to be measurable;

and *d(t)* is the unknown external disturbance. To be controllable, it is required that $g(\underline{x}) > 0$ for $\underline{x}$ in certain controllability region $U_c \subset R^n$ and that *d(t)* has upper bound *D*; that is, $|d(t)| \le D$. The detailed descriptions of each control part are exhibited in the following subsections.

B. FPIDSMC Design

The control problem is to push the state $\underline{x}$ to track a desired state vector $\underline{x}_d = (x_d, \dot{x}_d, \cdots, x_d^{(n-1)})^T \in \Re^n$. The tracking error is defined as

$$\underline{e} = \underline{x} - \underline{x}_d = (e, \dot{e}, \ddot{e}, ..., e^{(n-1)})^T \tag{2}$$

Now, a PID sliding surface is designed as following scalar equation

$$S = \underline{a}^T \dot{\underline{e}} + \underline{b}^T \underline{e} + \underline{c}^T \int \underline{e} d\tau \tag{3}$$

where

$\underline{a} = (a_0, a_1, a_2, \cdots, a_{n-1})^T$, $\underline{b} = (b_0, b_1, b_2, \cdots, b_{n-1})^T$ and $\underline{c} = (c_0, c_1, c_2, \cdots, c_{n-1})^T$

All the elements of following series sequence must be real number and satisfy the Routh-Herwitz condition.

$$\begin{aligned}&(c_0, b_0 + c_1, a_0 + b_1 + c_2, a_1 + b_2 + c_3, ..., a_{n-3} + b_{n-2} \\ &+ c_{n-1}, a_{n-2} + b_{n-1}, a_{n-1})\end{aligned} \tag{4}$$

The control effort as the solution of *S*=0 without considering the uncertainties is to achieve the desired performance under nominal model, and it is referred to as nominal control effort as follows:

$$u_0 = \frac{1}{g(x)}[-K + x_d^{(n)} - f(x)] \tag{5}$$

where

$$K = c_0 \int e d\tau + (b_0 + c_1)\dot{e} + \sum_{i=0}^{n-3} (a_i + b_{i+1} + c_{i+2}) e^{(i)} + (a_{n-2} + b_{n-1}) e^{(n-1)}$$

with the consideration $a_{n-1} = 1$.

However, if uncertainties occur then the nominal control effort cannot guarantee the desired performance and an auxiliary control effort should be added to eliminate the effect of the unpredictable perturbation. Let the sliding surface, *S*, be the input linguistic variable of the fuzzy logic, and the total control effort, *u*, be the output linguistic variable. The associated fuzzy sets for *S* and *u* are designed as follow:

For *S*: P (Positive), N (Negative), Z (Zero)

For *u*: DU (Decreased control effort), NU (Nominal control effort), IU (Increased control effort)

Then, the fuzzy linguistic rule base involved can be summarized as

Rule 1: If *S* is P then u is DU

Rule 2: If *S* is Z then u is NU

Rule 3: If *S* is N then u is IU

The triangular membership functions and center average defuzzification method are adopted in the proposed tracking inference mechanism. The membership functions of *S* and *u* are depicted in Fig. 1, respectively. After some mathematical manipulations, the total control effort can be obtained as

$$\hat{u} = w_1(u_0 - c) + w_2 u_0 + w_3(u_0 + c) \tag{6}$$

where $u_0 - c$, u_0 and $u_0 + c$ are the center of the membership function DU, NU and IU, respectively, in which $c > 0$ is the adjustable term; $0 \le w_1 \le 1$, $0 \le w_2 \le 1$, and $0 \le w_3 \le 1$ are the firing strength of Rule 1, 2 and 3, respectively. Note that, since the fuzzy sets for *S* are triangular membership functions and the relation $w_1 + w_2 + w_3 = 1$ is valid, equation (6) can be simplified as

$$\hat{u} = u_0 + c(w_1 - w_3) \tag{7}$$

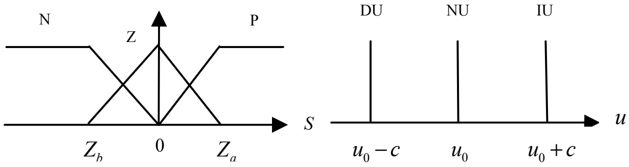


Figure 1. Membership functions of *S* and *u*

Consider a Lyapunov function candidate

$$V = \int sign(S) S d\tau = \int |S| d\tau \tag{8}$$

where *S* is the PID sliding surface. Differentiating *V* with respect to time, we can obtain

$$\begin{aligned}\dot{V} &= sign(S)S = sign(S)[K + e^{(n)}] \\ &= sign(S)[K + f(\underline{x}) + g(\underline{x})\hat{u} + d(t) - x_d^{(n)}]\end{aligned} \tag{9}$$

Substituting equations (5) and (7) into equation (9) yields

$$\begin{aligned}\dot{V} &= sign(S)[g(\underline{x})c(w_1 - w_3) + d(t)] \\ &= sign(S)g(\underline{x})c(w_1 - w_3) + sign(S)d(t) \\ &\le sign(S)g(\underline{x})c(w_1 - w_3) + |d(t)|\end{aligned} \tag{10}$$

From the relationships among *S*, w_1 and w_3, following conditions can be further concluded.

Condition 1: If *S*>0 then $w_1 = 0, w_3 > 0$,

such that $sign(S)(w_1 - w_3) = w_1 - w_3 < 0$.

Condition 2: If $S < 0$ then $w_3 = 0, w_1 > 0$,

such that $sign(S)(w_1 - w_3) = -(w_1 - w_3) < 0$.

Thus

$$sign(S)(w_1 - w_3) = -|w_1 - w_3| \tag{11}$$

And equation (10) can be rewritten as follow

$$\begin{aligned}\dot{V} &\le -g(\underline{x})c|w_1 - w_3| + |d(t)| \\ &= -[g(\underline{x})c|w_1 - w_3| - D]\end{aligned} \tag{12}$$

If the following inequality

$$g(\underline{x})c|w_1 - w_3| \ge D \tag{13}$$

holds, then the sliding condition $\dot{V} \le 0$ can be satisfied. As a result, the asymptotic stability can be assured under some specific conditions.

C. Adaptive Tuner Design

Although the performance of the system can be improved after using the fuzzy rule base, but it's still difficult to choose the optimal parameter of membership function. To solve this problem, a dynamic adaptation mechanism was added into the FPIDSMC. In this study, term *c* is designed as a tunable parameter and the Lyapunov stability theorem is utilized to derive the adaptive law. Now, equation (7) can be modified as

$$\hat{u} = u_0 + \hat{c}(w_1 - w_3) \tag{14}$$

where $\hat{c}$ is the estimate value of parameter c. Assume c^* is the optimal value of c and $\tilde{c} = \hat{c} - c^*$ is the estimated error.

To derive the adaptive law, following Lyapunov function candidate is considered

$$V_a = \int |S|\, d\tau + \frac{g(x)\alpha\tilde{c}^2}{2} \tag{15}$$

where α is a positive constant. Differentiating V_a with respected to time, we can obtain

$$\begin{aligned}
\dot{V}_a &= sign(S)S + g(\underline{x})\alpha\tilde{c}\dot{\hat{c}} \\
&= -[g(\underline{x})\hat{c}\,|w_1 - w_3| - d(t)] + g(\underline{x})\alpha\tilde{c}\dot{\hat{c}} \\
&= -g(\underline{x})\,|w_1 - w_3|\,[\hat{c} - c^* + c^* - \frac{d(t)}{g(\underline{x})\,|w_1 - w_3|}] + g(\underline{x})\alpha\tilde{c}\dot{\hat{c}} \\
&= -g(\underline{x})\,|w_1 - w_3|\,[\tilde{c} + \frac{D}{g(\underline{x})\,|w_1 - w_3|} + \varepsilon - \frac{d(t)}{g(\underline{x})\,|w_1 - w_3|}] + g(\underline{x})\alpha\tilde{c}\dot{\hat{c}} \\
&\le -g(\underline{x})\,|w_1 - w_3|\,[\tilde{c} + \varepsilon] + g(\underline{x})\alpha\tilde{c}\dot{\hat{c}} \\
&= -g(\underline{x})\,|w_1 - w_3|\,\varepsilon + g(\underline{x})\tilde{c}[\alpha\dot{\hat{c}} - |w_1 - w_3|]
\end{aligned} \tag{16}$$

If the adaption law for c is designed as:

$$\dot{\hat{c}} = \frac{|w_1 - w_3|}{\alpha} \tag{17}$$

then equation (16) becomes

$$\dot{V}_a \le -g(\underline{x})\,|w_1 - w_3|\,\varepsilon \tag{18}$$

According to $g(\underline{x})\,|w_1 - w_3|\,\varepsilon > 0$, one can obtain that $\dot{V}_a \le 0$. This means that the system will be still stable if the adaptation law for parameter c is tuned by equation (17). The overall scheme of the proposed AFPIDSMC tracking system is depicted in Fig. 2.

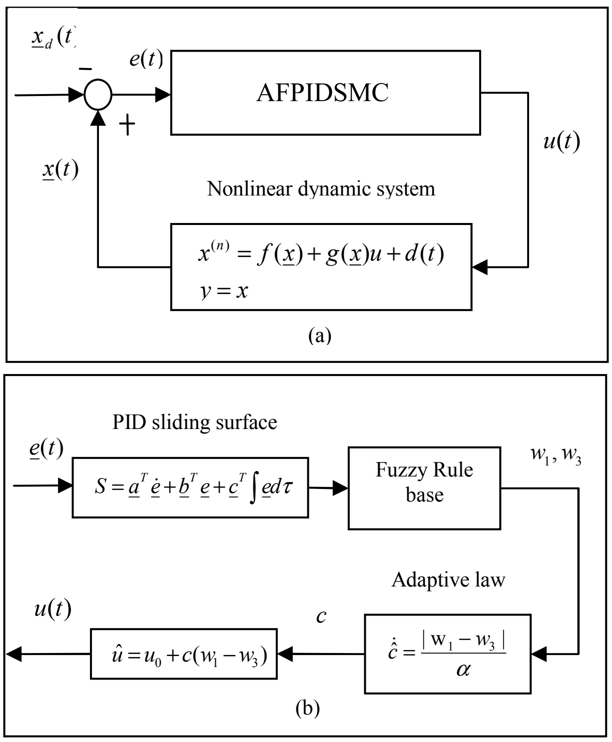


Figure 2. Overall scheme of the proposed AFPIDSMC tracking system. (a) whole control system; (b) AFPIDSMC strategy

III. Path Tracking For Wheeled Robot

A. *Kinematic Dynamics of Wheeled Robot*

The structure and parameters of a wheeled robot is shown in Fig. 3; the kinematic equation of a wheeled robot can be represented as [16]

$$\begin{aligned}
\dot{x} &= \frac{r\cos(\phi)}{2}(V_R + V_L) \\
\dot{y} &= \frac{r\sin(\phi)}{2}(V_R + V_L) \\
\dot{\phi} &= \frac{r}{2\eta}(V_R - V_L)
\end{aligned} \tag{19}$$

where $\dot{x}$, $\dot{y}$, r, η, ϕ, V_R, and V_L denote the proceeding distance change in x-axis, y-axis, radius of wheel, half width of the chassis, proceeding angle of robot's heading direction, speed of right and left wheel respectively.

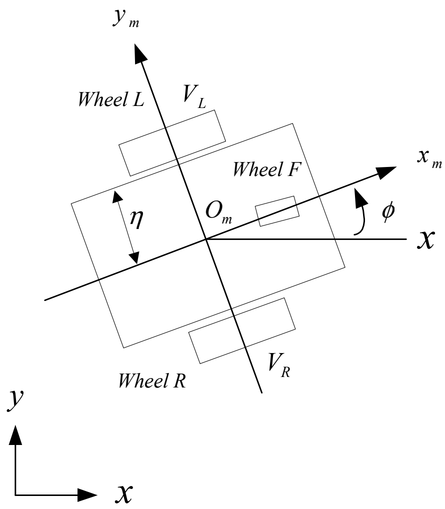


Figure 3. Structure and parameters of a wheeled robot

Consider equation (19) parametric variation, computing error due to unpredicted uncertainties for the actual wheeled robot

$$\begin{aligned}
\dot{x} &= \bar{r}\cos(\bar{\phi})V_R - \bar{\eta}\cos(\bar{\phi})\dot{\bar{\phi}} + L_x \\
\dot{y} &= \bar{r}\sin(\bar{\phi})V_L + \bar{\eta}\sin(\bar{\phi})\dot{\bar{\phi}} + L_y
\end{aligned} \tag{20}$$

where L_x and L_y are the total uncertainty for x-axis and y-axis, respectively. Here the bound of the total uncertainty is assumed to be given; that is,

$$|L_x| < \rho, \quad |L_y| < \rho \tag{21}$$

where ρ is a given positive constant.

B. *AFPIDSMC Path Tracking*

The purpose of the path tracking system is to make the robust following to the desired path. The path tracking error may occur due to command error, sluggish transformation, variation of robot parameters, friction, bumpy condition or transmitting efficiency etc. To track the prescribed path smoothly, a robust tracking scheme must be embedded into controller to calibrate the proceeding path simultaneously. In Elie *et al.* [17] and Jang [18], the angle and distance errors were fed into conventional controllers to modify robot's proceeding path. However, the tracking performance was not satisfactory because there existed with the chattering phenomenon and longer response time. In the past four decades, fuzzy systems have supplanted conventional technologies in many applications, especially in control systems. One major feature of fuzzy logic is its ability to express the amount of ambiguity in human thinking. Thus, it is appropriate to apply fuzzy logic to steer the wheeled robot because the accurate mathematical model doesn't exist and the uncertainties occur [10-15]. To further promote its tracking performance, the proposed AFPIDSMC scheme is applied to the wheeled robot to track the planned path simultaneously.

Now, let the desired location of the wheeled robot be a pair of two parameters (x_d, y_d) and the actual location be expressed by a pair of two parameters (x, y) which are defined in equation (20). Consider the x-axis, the tracking error and sliding surface are shown as

$$e_x = x - x_d \tag{22}$$

$$S_x = \lambda_1 \dot{e}_x + \lambda_2 e_x + \lambda_3 \int e_x d\tau \tag{23}$$

Then the speed command of right wheel under nominal model, represented by V_{Rn}, can be represented as

$$V_{Rn} = \frac{\dot{x}_d - \lambda_1^{-1}(\lambda_2 e_x + \lambda_3 \int e_x d\tau) + \bar{\eta}\cos(\bar{\phi})\dot{\bar{\phi}}}{\bar{r}\cos(\bar{\phi})} \tag{24}$$

After applying the proposed AFPIDSMC to x-axis, the total control effort and adaptive law for right wheel is

$$V_{Rt} = V_{Rn} + \hat{c}_x(w_{1x} - w_{3x}) \tag{25}$$

$$\dot{\hat{c}}_x = \frac{\lambda_1 |w_{1x} - w_{3x}|}{\alpha} \tag{26}$$

where w_{1x}, w_{3x} are the firing strength of rule 1 and 3 in fuzzy rules base, respectively.

Then applying the AFPIDSMC to y-axis, the nominal control effort, total control effort and adaptive law for left wheel can be expressed as

$$V_{Ln} = \frac{\dot{y}_d - \lambda_1^{-1}(\lambda_2 e_y + \lambda_3 \int e_y d\tau) - \bar{\eta}\sin(\bar{\phi})\dot{\bar{\phi}}}{\bar{r}\sin(\bar{\phi})} \tag{27}$$

$$V_{Lt} = V_{Ln} + \hat{c}_y(w_{1y} - w_{3y}) \tag{28}$$

$$\dot{\hat{c}}_y = \frac{\lambda_1 |w_{1y} - w_{3y}|}{\alpha} \tag{29}$$

C. Simulation Results

The simulation of the proposed system is carried out using "Matlab" package and the control parameters are given as

$$\lambda_1 = 1, \lambda_2 = 1, \lambda_3 = 2, \bar{r} = \bar{\eta} = 5cm \tag{30}$$

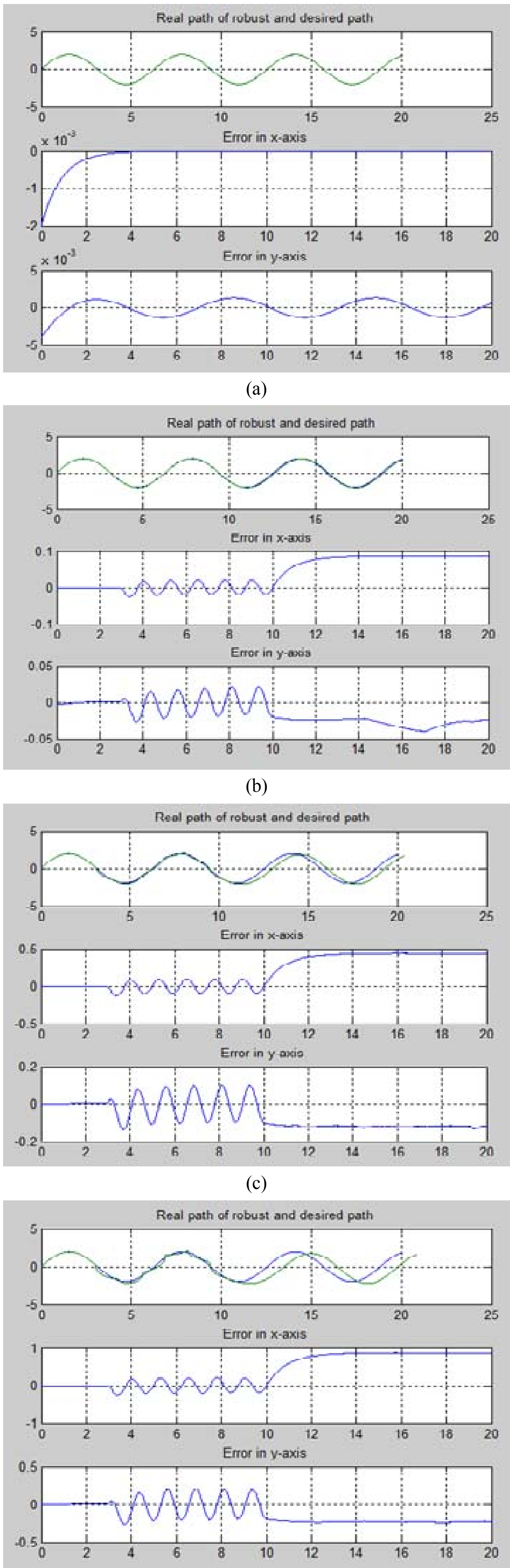
All the parameters in the proposed control systems are chosen to achieve the requirement of stability and actual specification. Four simulation cases including parameter variations and external disturbance in the kinematic equation due to periodic sinusoidal commands are addressed as follows:

Case 1: without uncertainties.

Case 2: $L_x = 0.1\cos(5t)$, $L_y = 0.1\sin(5t)$.

Case 3: $L_x = 0.5\cos(5t)$, $L_y = 0.5\sin(5t)$.

Case 4: $L_x = \cos(5t)$, $L_y = \sin(5t)$.



(a) (b) (c) (d)

Figure 4. Simulated results of conventional AFSMC tracking system.

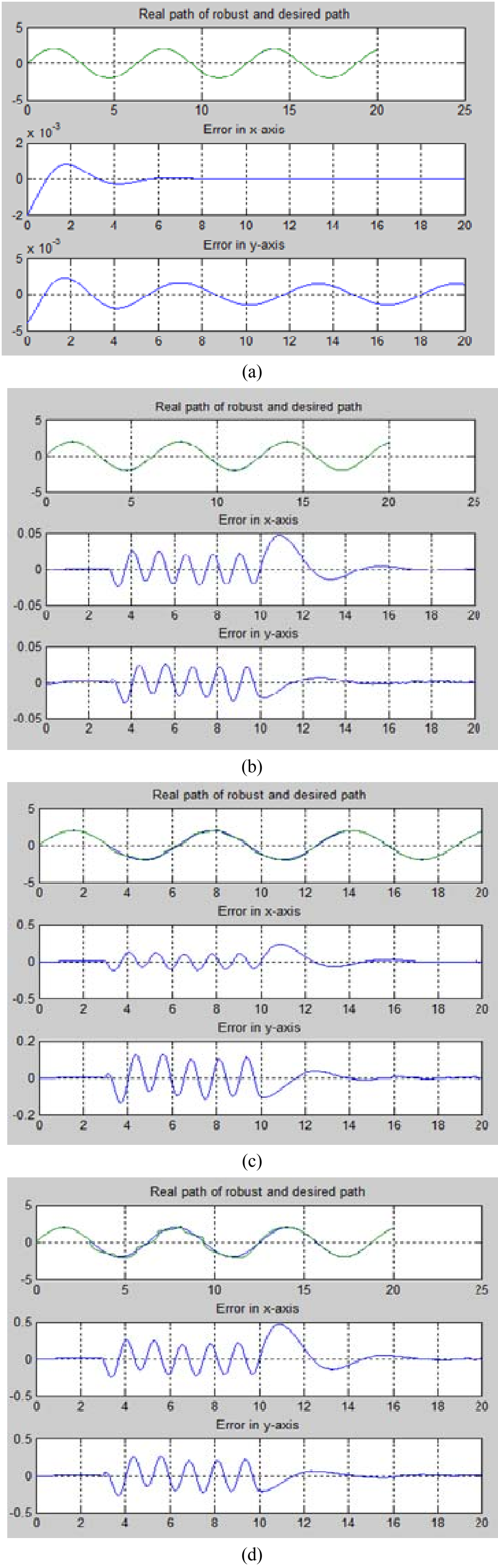


Figure 5. Simulated results of proposed AFPIDSMC tracking system.

Now, the conventional AFSMC tracking system [15] is considered first. The tracking responses of the AFSMC system due to periodic sinusoidal commands at Case 1, 2, 3 and 4 are depicted in Figs. 4(a), (b), (c) and (d), respectively. From the simulated results, there are no chattering phenomena, but degenerate tracking performances are resulted owing to the parameter variations and external disturbance. Finally, the proposed AFPIDSMC tracking system under rules 1, 2, 3 and the control law in equations (24, 25, 26, 27, 28 and 29) is considered. The tracking responses due to periodic sinusoidal command at Case 1, 2, 3 and 4 are depicted in Figs. 5(a), (b), (c) and (d), respectively. From the simulated results, not only there are no chattering phenomena but also favorable tracking response can be obtained under the occurrence of uncertainties. Compare Fig. 5 with Fig. 4, the proposed AFPIDSMC system is more suitable to track the desired path for a wheeled robot.

The similarities between the proposed architecture and other similar schemes, e.g. conventional AFSMC, etc., are that both of them are the combination of fuzzy control, sliding mode control and adaptive tuner. This combination can not only eliminate the disadvantages of all above methods, but also have better performance than the methods which only use fuzzy control (FC) or sliding mode control (SMC). The main disadvantage of the pure sliding mode controller is that there exists sudden and large change in the control effort during the process which leads to high stress for the system to be controlled. It also leads to chattering phenomenon of the system states. By combining SMC with FC, the change of control effort will be smoothened. On the other hand, the number of fuzzy rules in rule base is large if we just only use FC. By combining the SMC with FC, the number of rules becomes fewer and simple. In addition, by adding adaptive law into the controller, the parameter will be automatically updated to get the optimal values during the controlled period, thus the initial setting for the parameters is simple now.

The difference between the proposed architecture and other conventional AFSMCs is the definition of the sliding surface. The sliding surface included the error part and the derivative error part in conventional AFSMC while one in the proposed AFPIDSMC not only included above parts, but also included the integral part. By adding more integral element, the SMC part in controller has effectiveness even when the error is too small that can not affect error part, or the error take a long time to change that can not affect derivative part. Thus the steady error of system will be eliminated, the system will be more stable and the precision of the controller, which is very important in tracking controller, will be improved. We can see in the Figs. 5(a), (b), (c), (d), the steady errors in x-axis are approximately 0, 0.003, 0.01, 0.01 respectively, and the steady errors in y-axis are approximately 0.0015, 0.002, 0.001, 0.01 respectively. These values are much smaller and come closer zero value than those in Fig. 4. In the Figs. 4(a), (b), (c), (d), the steady errors in x-axis are approximately 0, 0.087, 0.44, 0.86 respectively, and the steady errors in y-axis are approximately 0.0014, 0.025, 0.12, 0.2 respectively. Although the time responses in both of two controllers are similar which are almost 4 seconds, but the precision of the proposed AFPIDSMC is better than conventional AFSMC.

CONCLUSIONS

In this study, an AFPIDSMC is proposed to attenuate the effects caused by unmodeled dynamics, disturbance and approximate error, for nonlinear dynamic system. The design principle is that a novel reinforced adaptive mechanism and the PIDSMC technique are incorporated into the fuzzy controller to strengthen its anti-disturbance ability. The proposed method possesses the advantages that it behaves like PIDSMC, can reduce the fuzzy rules like FSMC and can automatically adjust the membership function like AFC. In this study, the adaptive techniques are applied to the design of the stable fuzzy controller. This study has also demonstrated the application of the proposed scheme to steer the wheeled robot. Performance comparisons of the conventional AFSMC and proposed AFPIDSMC systems are carried out in this paper. From the results, it shows that the proposed AFPIDSMC yields superior control performance than the conventional AFSMC scheme.

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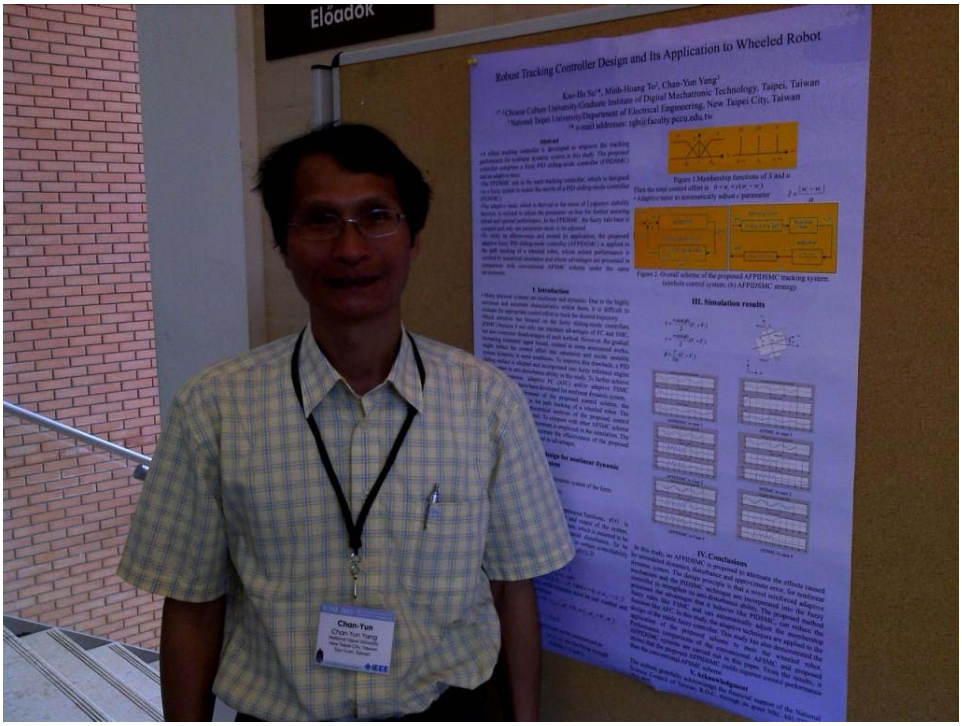

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