

C02018: Doctor of Philosophy

CRICOS Code: 036570B

49986 PhD Thesis: Engineering

May 2022

*A Study on
Model estimation for health monitoring and
rehabilitation systems*

Li Wang

School of Biomedical Engineering

Faculty of Engineering and Information Technology

University of Technology Sydney

NSW - 2007, Australia

A Study on
Model estimation for health monitoring
and rehabilitation systems

*A thesis submitted in partial fulfilment of the requirements
for the degree of*

Doctor of Philosophy
in
Engineering

by

Li Wang

to

School of Biomedical Engineering
Faculty of Engineering and Information Technology
University of Technology Sydney
NSW - 2007, Australia

May 2022

AUTHOR'S DECLARATION

I, *Li Wang* declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Biomedical Engineering, Faculty of Engineering and Information Technology* at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

SIGNATURE: _____
[Your Name]

DATE: 03rd May, 2022

PLACE: Sydney, Australia

ABSTRACT

Electronic trainers (e-trainers) are fitness guidance systems consisting of motion signal sensor(s), a user interface, and a control system. Owing to the widespread popularity of fitness and personal training, e-trainers have found numerous applications across many fields. However, the design of e-trainers is challenging because of their requirement for miniaturisation and problems with discrepancies, drift, lack of data, and limited resources. The primary aim of this thesis is to design an improved e-trainer with a focus on the initial measurement unit calibration algorithm and the practical implementation of pattern recognition algorithms. Several problems in the field are considered, including kernel-based heart rate regulation, practical considerations for the calibration of efficient wearable devices, and model compression using the pruning method.

The first part of this thesis investigates several practical issues associated with calibrating the proposed low-cost wearable e-trainer in clinical settings, including poor repeatability and significant volatility. In field-based environments, the parameter variation of the low-cost triaxial gyroscope requires an effective and practical calibration process to reduce the errors due to unexpected variance. To this end, an efficient in-field calibration method is developed that can readily calibrate the triaxial gyroscope without additional equipment. This experimental scheme can be easily implemented by manually rotating the triaxial gyroscope over a certain angle as the calibration reference. A linearised calibration model is developed for the proposed experimental scheme, and G-optimality is achieved. Extensive numerical simulations demonstrate that the calibration error is relatively low and the estimation of model parameters is unbiased under mild experimental conditions. After a calibration process taking less than 30 s, the absolute error of the scale factors is always less than 2.5×10^{-2} for LSM9DS1 and that of the biases is less than 1×10^{-2} for ICM20948.

In the second part of this thesis, to overcome the lack of suitable training data for modelling the human cardiovascular response, the simulation and control of the human heart rate are investigated in detail using a kernel-based nonparametric model with model predictive control. This kernel-based method introduces a kernel regularisation term that provides prior information to the model estimation phase. By adding this prior information, the experimental protocol can be significantly simplified, with a model training time of only 10 min. Based on the identified model, a controller that uses model predictive control is designed to track a predefined reference heart rate profile. One

advantage of this approach is that the speed and acceleration of the treadmill can be maintained within a safe range for vulnerable exercisers. The entire model construction process takes 10 min, including an 80-s resting period. The protocol is relatively simple and consists of only two accelerations. In the heart rate tracking task, the heart rates of 12 experiment participants follow the target heart rate to within ± 3 beats per second.

The third part of this thesis leverages the state-of-the-art neural network pruning method to compress the network model. This allows the computational complexity of the inference task to be reduced by 98% without significant performance degradation. It is therefore possible to use advanced deep learning models to estimate human motion states on embedded systems with limited resources. For the user, more neural network models operating on the device means that more functions can be provided. Experimental results verify the effectiveness and efficiency of the proposed method, with up to 60% of graph links and 98% of network weights pruned across different tasks with no significant drop in accuracy.

An application of the proposed e-trainer is introduced in the fourth part of this thesis. The purpose of this application is to estimate the gait parameters (i.e. contact time (CT) and flight time (FT)) of 40 rugby players associated with the Sydney Swans Football Club. This is important because the analysis of such gait parameters can help players increase their running performance and reduce the running-related injury risk. In addition to the CT and FT, a pre-processing system that detects the running period and identifies the 95% confidence interval is introduced to analyse and enhance the detection accuracy. We also investigate the compatibility of CT and FT estimation based on the data collected from a gyroscope and an accelerometer placed in a single location. The results show that the combined accelerometer–gyroscope system obtains the desired accuracy (absolute error < 20 ms) in CT and FT detection. Moreover, after introducing the confidence interval, the two systems exhibit high consistency at lower running speeds (< 20 km/h).

In conclusion, this thesis describes a comprehensive solution for the design of both hardware and software for electronic virtual trainers. The first part presents an efficient calibration method for gyroscopes. This method only requires simple external devices (or may not need any external device), and can be finished within 30 s. The gyroscope reading accuracy is significantly enhanced by the use of our method. The second part aims to overcome the problem of a lack of data using kernel-based modelling. For users, fewer experiments are needed during the model building period. For the issue of limited resources, the fourth part proposes a model compression method for complex neural networks operating on resource-limited embedded systems. Thereby, novel machine learning algorithms can provide additional guidance to the user.

ACKNOWLEDGMENTS

There are many key points in life, and there are many people and many thanks to keep in mind. First and foremost, I would like to express my most sincere gratitude to my principal supervisor, A/Prof. Steven Su, for his continued support and wise guidance throughout my Ph.D. study. His knowledge, expertise, understanding, and insights greatly expanded my knowledge and skills in many areas. His patience and optimism helped me through the ups and downs of the Ph.D. life. Without his persistent help, the goal of this research would not have been achieved.

I would also like to show my great appreciation to my co-supervisor, Prof. Ren Ping Liu, for his solid support and skilful guidance. His expertise, intelligence, and encouragement enlarged my vision to a broader field and steered me to dive deeper into my research.

Many thanks to the School of Biomedical Engineering, Faculty of Engineering and Information Technology. The friendly and helpful staffs at the school create a great environment for the research study. The resources provided by the school and the faculty is the key of the success in the research.

Additionally, I would like to express gratitude to Dr. Miao Zhang for his treasured support which was really influential in shaping my experiment methods and critiquing my results. Dr. Taoping Liu is an inspiring colleague, blazing a trail I followed in writing my thesis. I also thank Dr. Kairui Guo, Dr. Wei Huang and Dr. Hairong Yu for their mentorship. I would like to thank my friends, colleagues and research team - Feng Shan, Haoding Xu, Jephil Palayil, and Dr. Feng Gao for a cherished time spent together in the lab, and in social settings.

Last but not least, I am grateful for having my wife and my family to support my research journey.

LIST OF PUBLICATIONS

PUBLISHED :

1. **Wang, L.**, Yang, Y., & Su, S. (2021, November 1-5). *Nonparametric Modelling Based Model Predictive Control for Human Heart Rate Regulation during Treadmill Exercise*. 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Guadalajara, Mexico.
2. **Wang, L.**, Zhang, T., Ye, L., Li, J. J., & Su, S. (2021). An Efficient Calibration Method for Triaxial Gyroscope. *IEEE Sensors Journal*. doi: 10.1109/JSEN.2021.3100589.
3. Yang, Y.¹, **Wang, L.**¹, Su, S., Watsford, M., Wood, L., & Duffield, R. Inertial Sensor Estimation of Initial and Terminal Contact during In-Field Running. *Sensors*.

UNDER REVIEW :

3. **Wang, L.**, Fox, D., Duffield, R., Hammond, A., Zhang, A., & Su, S. An Infield Gyroscope Calibration Method In Wearable Health Monitoring. Submitted to *IEEE Transactions on Systems Man Cybernetics-Systems*.
4. **Wang, L.**¹, Huang, W.¹, Zhang, M., & Su, S. Pruning Graph Neural Network by Evaluating Edge Property. Submitted to *Knowledge-Based Systems*.
5. Zhang, M., **Wang, L.**^{*}, Campos, D., Huang, W., Guo, C., & Yang, B. Weighted Mutual Learning with Diversity-Driven Model Compression. Submitted to *NeurIPS 2022*.
6. Huang, W.¹, **Wang, L.**¹, Wang, S., & Zhang, M. Can Wide Variational Auto-encoder Generate? Submitted to *NeurIPS 2022*.

-
7. Liu, T., Zhang, W., **Wang, L.**, Ueland, M., Forbes, S., Zheng, W., & Su, S. Numerical Differentiation from Noisy Signals: A Kernel Regularization Method to Improve Transient-State Features for the Electronic Nose. Submitted to *IEEE Transactions on Systems Man Cybernetics-Systems*.

UNDER PREPARATION :

9. **Wang, L.**, & Su, S. On the Influence of Rotation Speed and Noise Intensity of the Calibration Accuracy of Gyroscope. Prepare submit to *IEEE Transactions on Industrial Electronics*.

TABLE OF CONTENTS

List of Publications	vii
List of Figures	xiii
List of Tables	xix
1 Introduction	1
1.1 Motivation and Scope	1
1.2 Design Challenges and Solution Strategy	4
1.2.1 Challenges in Using Inertial Measurement Unit	5
1.2.2 Challenges in Implementing Pattern Recognition Algorithms	7
1.3 Influence of COVID-19	9
1.4 Thesis Contributions	10
1.5 Thesis Outline	15
2 Literature Review	19
2.1 Review of Physiological Signal Response Modelling	19
2.1.1 Nonparametric Dynamical Models	19
2.1.2 Artificial Neural Network Models	21
2.2 Review of Inertial Measurement Units	24
2.2.1 Working Principle	25
2.2.2 Main Performance Parameters	27
2.2.3 Types of Gyroscope	28
2.2.4 Gyroscope Calibration	32

TABLE OF CONTENTS

2.3	Review of Model Compression Methods for Pattern Recognition Algorithms	35
2.3.1	Pruning Target	35
2.3.2	Pruning Methods	37
3	Triaxial Gyroscope Calibration via Servomotor	39
3.1	Introduction	39
3.2	Calibration methodology	41
3.2.1	Efficient Calibration Method for Triaxial Gyroscope	41
3.2.2	G-Optimal Experimental Design	45
3.3	Simulation	46
3.3.1	Simulation Under Normal Conditions	47
3.3.2	The Effect of Rotation Speed	51
3.3.3	Robustness of the Method under Extreme Conditions	52
3.4	Experiments	55
3.4.1	Calibration of Two Low-cost Gyroscopes	56
3.5	Conclusion	58
4	Triaxial Gyroscope Calibration via Manual Rotation	61
4.1	Introduction	61
4.1.1	Preliminary Study	62
4.1.2	Pre-study	64
4.1.3	Existing Calibration Methods	65
4.1.4	Summary of Our Contributions	66
4.2	Methodology	66
4.2.1	Calibration principle	68
4.2.2	Model Linearization and Experimental Design	69
4.2.3	Summary of the calibration process	72
4.3	Simulation	73
4.4	Experiments	75
4.4.1	Experiments Device and Hardware Design	75

4.4.2	Experimental Setting	76
4.4.3	Comparing with existing calibration methods	77
4.4.4	Results and discussion	78
4.5	Conclusion	80
5	Nonparametric Modelling Based Human Heart Rate Regulation	83
5.1	Introduction	83
5.2	Kernel-based estimation method of heart rate response model	85
5.3	MPC Controller Design	87
5.4	Experiments and Discussion	88
5.4.1	Experimental Equipment	89
5.4.2	Model Estimation	89
5.4.3	MPC Heart Rate Regulation	91
5.5	Conclusion	92
6	Model compression via pruning method	95
6.1	Introduction	95
6.2	Preliminaries	98
6.2.1	Graph Neural Networks	99
6.2.2	Network Pruning	100
6.3	Theoretical Framework	100
6.3.1	Formulations	101
6.3.2	An Error Bound for GNNs through Graph Spectral theory	102
6.3.3	Edge Property Matters	103
6.4	Build Effective Pruning Method for GNNs	104
6.4.1	Revisit Graph Lottery Ticket	104
6.4.2	Pruning Graph via Edge Property	106
6.4.3	Pruning Graph via Edge Property	106
6.4.4	A General Two-Step Pruning Method for GNNs	107
6.5	Experiments	107

TABLE OF CONTENTS

6.5.1	Dataset	108
6.5.2	The Training-free Pruning Methods on GNNs	108
6.5.3	Ablations for graph pruning methods	110
6.5.4	A General Two-Step Pruning Method for GNNs	112
6.5.5	Ablations on pre-trained GNNs	112
6.5.6	Complementary experiments	114
6.5.7	Large-scale Graphs with 28-layers ResGCN	118
6.6	Findings	118
6.7	Conclusion	119
7	Reliable temporal gait parameter estimation	121
7.1	Introduction	121
7.2	Method	123
7.2.1	Data pre-processing	123
7.2.2	Algorithm design	124
7.3	Results and Discussion	130
7.3.1	Data collection Protocol	130
7.3.2	Data Pre-processing	131
7.3.3	Algorithm consistency	133
7.3.4	Accuracy of Detection	134
7.4	Discussion	136
7.5	Conclusions	138
8	Conclusion and Future Work	141
8.1	Conclusion	141
8.2	Future Work	143
	Bibliography	145

LIST OF FIGURES

FIGURE	Page
1.1 Left: Common sports band. Right: Fit.E, designed by the candidate.	3
1.2 Research directions of virtual personal trainers. Red rectangles indicate the focus of this study.	4
1.3 Summary of the design challenges and thesis outline.	5
1.4 Turntable calibration system [1].	6
1.5 Functional block diagram of Fit.E.	11
1.6 Left: Interior of Fit.E. Right: Exterior of Fit.E.	11
1.7 Left: AIE XO system architecture. Right: Embedded control board in hand. . .	12
1.8 Prototype of the AIE XO.	13
2.1 Mathematical model of an artificial neuron.	21
2.2 Ideal activation function: Unit step function.	22
2.3 Commonly used activation functions.	23
2.4 Typical neural network with one hidden layer.	24
2.5 Rotation coordinate system.	26
2.6 MEMS gyroscope working principle.	26
2.7 Physical model of a typical tuning fork vibration gyroscope [2].	29
2.8 Physical model of vibrating shell gyroscope [2].	30
2.9 Schematic of the fluid-floated gyroscope [3].	30
2.10 Floated two-axis gyro schematic [3].	32
2.11 Taxonomy of existing gyroscope calibration methods.	33
2.12 Camera-aided gyroscope calibration method.[4]	33

LIST OF FIGURES

2.13	Magnetometer-aided gyroscope calibration method.[5]	34
2.14	Accelerometer-aided gyroscope calibration method.[6]	34
2.15	Overview of neural network pruning.	36
2.16	Typical pruning method flowchart.	37
3.1	Six-observations rotation protocol for gyroscope calibration. The gyroscope is rotated at constant speed clockwise and counterclockwise along the x,y,z axis. [7]	44
3.2	The simulation results of estimation error between estimated and actual parameters under normal conditions at different noise level using different method. Top: 0.035 rad/s noise levels. Bottom: 0.2 rad/s noise level. Left: Levenberg-Marquardt (LM) method. Right: Our proposed method. [7]	46
3.3	Simulation results of the desired rotation speed ω and gyroscope readings from three axes x, y, z before and after calibration. The dashed line indicates actual rotation on each axis, and the solid line represents gyroscope readings. [7]	47
3.4	The mean squared error (MSE) between estimated and actual parameters at different rotation speeds during calibration with different measurement noise levels. (a) 0.035 rad/s noise level. (b) 0.2 rad/s noise level. [7]	49
3.5	The simulation results of estimation error between estimated and actual parameters under extreme conditions at different noise level using different method. Top: 0.035 rad/s noise levels. Bottom: 0.2 rad/s noise level. [7]	50
3.6	Experimental system for the gyroscope calibration on a robot arm UR10e. The part names and joint numbers are noted. [7]	52
3.7	Raw gyroscope data from LSM9DS1, compared with ADIS16465 reading during calibration. (a) Periodic vibration was caused by the control strategy of the servomotor. (b) The component on the non-rotating axis was caused by mounting misalignment. [7]	53

3.8	Raw gyroscope data from MPU9250, compared with ADIS16465 reading during calibration. (a) Periodic vibration was caused by the control strategy of the servomotor. (b) The component on the non-rotating axis was caused by mounting misalignment. [7]	54
3.9	Calibrated gyroscope data from LSM9DS1, compared with ADIS16465 reading during the testing period. (a) The reading from LSM9DS1 and ADIS16465 nearly coincided with each other. (b) The biases of gyroscope reading were almost zero. [7]	54
3.10	Calibrated gyroscope data from MPU9250, compared with ADIS16465 reading during the testing period. (a) The reading from MPU9250 and ADIS16465 nearly coincided with each other. (b) The biases of gyroscope reading were almost zero. [7]	55
4.1	The designed wearable motion tracking device	62
4.2	The designed device using in the pilot study	62
4.3	Estimated orientation using raw gyroscope readings before calibration from two models of gyroscope. Left: LSM9DS1. Right: ICM20948.	64
4.4	The taxonomy chart of existing gyroscope calibration methods.	65
4.5	The orientation estimation tests. The IMU is mounted on a robot arm.	67
4.6	4-observations rotation protocol for gyroscope calibration. (1) Stationary stage. (2)-(4) Rotating stage: Manually rotate the gyroscope 360 degrees clockwise along the x,y,z axis.	67
4.7	Typical simulated measurements of the proposed calibration method under $0.15^\circ/sec$ noise level. Speed variation and speed projection on non-rotating axis were to simulate the manual rotation process.	70
4.8	The error of estimated biases and scale factors compared with the true values at different noise levels. (a) $0.03^\circ/sec$ noise level. (b) $0.15^\circ/sec$ noise level.	72
4.9	The mean error of the calibrated angular velocity compared with the actual value of each axis. Row: under different noise levels. Column: before and after calibration.	73

LIST OF FIGURES

4.10	Experimental system for gyroscopes calibration. Main figure: the initial position of the device. Top left figure: bottom view of the device.	75
4.11	The designed wearable motion tracking device functional block diagram.	76
4.12	Magnitude of rotation speed before and after calibration. The acceleration and deceleration phases were omitted.	79
4.13	Estimated orientation using calibrated gyroscope readings after calibration from two models of gyroscope. Left: LSM9DS1. Right: ICM20948.	79
5.1	The proposed automatic treadmill system and speed profile during the identification period. (A) Resting. (B) Walking.[8]	84
5.2	Schematic of the automatic treadmill system [8]	85
5.3	(Top) Typical estimated heart rate comparison between Kernel method and LS method. (Bottom) The estimated impulse response for one participant. [8]	90
5.4	Heart rate tracking results for all 12 subjects. [8]	92
6.1	Pruning-at-initialization Methods performance when jointly pruning graph links and network weights over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora. Note: GraSP is no draw when layer collapse occurs.	108
6.2	Pruning-at-initialization Methods performance when solely pruning network weights over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora, Citeseer, and PubMed datasets, respectively.	110
6.3	The General Two-Step Pruning method performance when jointly pruning graph links and network weights over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora.	111
6.4	Pruning-at-initialization Methods performance when jointly pruning graph links and network weights over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora, Citeseer, and PubMed. Note: GraSP is no draw when layer collapse occurs.	115

6.5	Pruning-at-initialization Methods performance when solely pruning graph edges over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora, Citeseer, and PubMed datasets, respectively.	116
6.6	The performance of 28-layer deep ResGCN on large-scale graph data set.	116
6.7	The General Two-Step Pruning method performance when jointly pruning graph links and network weights over achieved graph sparsity levels and network sparsity of GCN, GIN, and GAT on Cora, Citeseer, and PubMed	117
7.1	Random samples of right ankle acceleration value in g A_{ankleR} of a participant during 10km/h running. Note: the peak resultant acceleration is marked as IC, and the 2g-threshold is the area of interest for TC detection.	125
7.2	Random samples of right ankle angular rate ω_{ankleR} of a participant during 10km/h running. Note: MS = Mid-Swing; IC = Initial-Contact; TC = Terminal-Contact.	127
7.3	The placement of the IMU device on the ankle area of a participant.	131
7.4	Random sample of a participant's pre-processed data with three different running speeds (10km/h, 15km/h and 20km/h).	132
7.5	Comparesion between actual result (red line) and estimated results (dots). Note: MS = Mid-Swing; IC = Initial-Contact; TC = Terminal-Contact.	134

LIST OF TABLES

TABLE	Page
3.1 Convergence rate under different scale factors and biases	52
3.2 Comparison of LSM9DS1 calibration results	57
3.3 Comparison of MPU9250 calibration results	57
3.4 MSE between LSM9DS1 and ADIS16465	57
3.5 MSE between MPU9250 and ADIS16465	58
4.1 Related parameters of test gyroscope	76
4.2 Calibration results comparison of LSM9DS1.	77
4.3 Calibration results comparison of ICM20948	77
5.1 Participant information.	88
5.2 Fitness error.	91
6.1 Test accuracies on Cora, Citeseer, PubMed for different pruning-at-initialization methods when jointly pruned 98% weights and 60% graph links.	109
6.2 Dataset Statistics	109
6.3 Test accuracies on Cora, Citeseer, PubMed for the General Two-Step Pruning methods at different sparsities.	112
6.4 Performance compare by applying SNIP, and SynFlow before training (BF) and after training (AT). Pruned ratio: 95%.	113
7.1 The detection logic and conditions for IC, MS and TC detection.	128

LIST OF TABLES

7.2	The consistency of the two systems under different speeds and maximum tolerance values of the confidence interval.	133
7.3	The mean error of the two algorithms under different speeds.	134
7.4	The consistency of the two systems under different speed and maximum tolerance value of the confidence interval.	135