

EMG Control Strategy of a Cable-based Upper Limb Rehabilitation Robot and its Verification

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Thesis submitted in fulfilment of the requirements for
the degree of

Doctor of Philosophy

under the supervision of Steven Su

University of Technology Sydney
Faculty of Engineering and Information Technology

September 2020

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Yao Huang 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.

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Acknowledgements

I would like to express my sincere gratitude to my supervisor A/Prof. Steven Su for his continual support, guidance, help, and encouragement during my Ph.D. study. Dr. Su has brought me into the topic of rehabilitation robot control strategies and provided brilliant insights into my research works. It is my honor to have a supervisor who always inspires me to achieve higher targets. His conscientious and meticulous attitude on research has a significant influence on my work.

I am grateful to my co-supervisor, Dr. Trang Nguyen, for her kind support and constructive suggestions on my research. I would also like to thank my external supervisor Prof. Hung Nguyen (Swinburne University of Technology), Prof. Rong Song (Sun Yat-sen University, China), and Dr. Ahmadreza Argha (The University of New South Wales) for their support in providing platform and opportunities and their constructive advice to my research. I would also deeply appreciate Prof. Branko G Celler (The University of New South Wales) and Prof. Andrey V Savkin (The University of New South Wales) for their precious guidance and contribution to my chapters. I would also like to thank Prof. Daniel P. Ferris (University of Florida, USA) and Ms. Kara McArthur for the valuable comments and delicate editing on my publications.

I also wish to express my appreciation to the staff members in the Centre for Health Technologies, School of biomedical engineering, University of Technology Sydney, especially to Prof. Joanne Tipper, Prof. Gyorgy Hutvagner, and Dr. Steve Lin. I have received a unique and memorable experience to work with these professional and inclusive people.

I am grateful to my colleagues in A/Prof. Steven Su's research group, in particular, Dr. Lin Ye, Dr. Wentian Zhang, Dr. Wenhui Chen, Dr. Hairong Yu, Kairui Guo,

Taopin Liu, Miao Zhang, Yujiao Wu, Linneng Li, and Li Wang, for their selfless help and technical support. Working together with them brings a lot of happiness and a good memory for me. I would also be grateful to my colleagues in Prof. Rong Song's research group, in particular, Dr. Qianqian Yang, Yuanyu Wu, Ying Chen, Yu Zhuang, Na Tian, Jie Zhou, Xianming Li, Tian Xie, Chenlin Xie, Lefei Zhou, and Qiurong Deng for their great help in our cooperation project. I also sincerely appreciate my friends, Dr. Zhichao Sheng, Dr. Ye Shi, Dr. Haimin Zhang, Zhiyuan Shi, Hanjie Wu, and Dr. Daniel Roxby, for their warm support.

Lastly, my deepest gratitude goes to my family and my boyfriend for their immeasurable support and encouragement throughout my graduate studies.

Abstract

Post-stroke motor recovery highly affected by patients' active participation in rehabilitation. Surface electromyography (EMG) signals are related to a subject's intention. It is also one of the most widely used biosignals in the area of motion intention estimation and rehabilitation robot control. However, due to the complicated relationship between multiple muscles and movements, few studies have applied continuous multiple EMG signals to control rehabilitation robots and provide assistant to users' multi-joint movements in real-time.

In this dissertation, new methods for decoding EMG signals during robot-assisted movements are proposed and applied to manipulate a cable-based rehabilitation robot. Different EMG decoders for continuously estimating voluntary motion intention are developed to fulfil different rehabilitation needs. These decoders are used to establish a human-robot cooperative control scheme for promoting users' active participation in rehabilitation.

Firstly, an EMG decoder is build up with a switching mechanism and submodels for decoding EMG signals to motion need forces during a multi-joint complex task in three-dimensional space. The switching mechanism aims to carve up the task into separate simple subtasks. For each simple subtask, a linear six-input three-output time-invariant submodel is established by the state-space modelling method. The inputs are the processed muscle activations of six arm muscles, and the outputs are motion need forces of users when executing the task with visual feedback. The outputs are used to indicate three motors of the robot. The switching logic of the mechanism is to change the parameters of each submodel by times. However, we observed a 'bump' behaviour of the estimated forces (i.e., discontinuity) when switching parameters of

two submodels. A sudden change in control signals of motors might cause unexpected impacts on patients, so it is unacceptable during rehabilitation.

After that, to improve the smoothness of the estimated forces, we attempted to maintain the continuity of the decoder outputs when switching among submodels. A bumpless switching mechanism is proposed by constructing a generic multirealisation for all submodels. The generic multirealisation has a common output matrix, which helps to continuously predict the outputs. For submodels with the same order, the multirealisation is constructed by finding the common denominator matrix of the subsystems' Matrix Fraction Description (MFD). Furthermore, the best submodel, in terms of goodness of fit, established in each simple subtask, may have a different order. For different-ordered submodels, the generic multirealisation is constructed by finding the common highest-degree-coefficient matrix and expanding the hidden states of submodels. To this end, the bumpless switching mechanism for achieving continuous outputs is achieved.

Finally, to expand the application of a rehabilitation robot, it is vital to use less and accurate EMG decoders for multiple tasks and to reduce the impact of individual differences. A decoder based on a time-variant long short-term memory (LSTM) network is proposed. We attempt to train one LSTM network for each time step, so the decoder is seen as a time-variant system. All parameters of the decoder are trained with error functions of both time step accuracy and task accuracy. This method does not need a secondary feature extraction or preprocessor and can be applied in real-time robot control.

The experiments for examining these decoders included model training, model testing, and online verification to control the robot in real-time. Healthy subjects who participate in the linear system-based EMG decoders and nonlinear system-based EMG decoders were instructed to perform different tasks in three-dimensional space with visual interactions.

Experimental results demonstrated that EMG decoders with the switching mechanisms and linear system-based submodels could effectively recognise arm motion intention and provide appropriate assistance to users. The outputs achieved by the bumpless switching mechanism with submodels are significantly smoother than those

without it. The bumpless switching mechanism can avoid users from the risk of unpredictable loads. These approaches performed well in specific subjects and tasks with no need for an immense database and complicated model parameters.

The results of the time-variant LSTM-based decoders showed that this nonlinear system approach outperforms linear system approaches in both model testing and online verifications. The complicated structure and well-trained parameters ensure that the nonlinear system approach does not need to take account of individual differences when applying in real-time. The findings also suggested that the time-variant LSTM system decoders may be feasible for practical use in both single and multiple complex tasks.

An investigation on the differences in recruited muscle patterns when users perform multi-joint multi-directional arm movements with the robot assistance or naturally without a robot is carried in this dissertation. The results indicated that both the natural and robot-assisted multi-joint movements could be generated by similar sets of synergies of limited dimensionality. This is a supportive finding that the proposed human-robot cooperative control strategy based on a proper EMG decoder may not significantly affect human motion control pattern while supporting users.

Furthermore, the effects of task variety and tracking accuracy by visual feedback on muscle synergies and their activation patterns were explored by statistic analysis. The results showed that, for active rehabilitation applications, if the purpose is to enhance the synergy indication from the neural system, the task completion accuracy should be emphasised. If the purpose is to expand the motion area, the task variety should be diversified. These results supported that different decoders should be used and developed to meet the different assistance requirements of post-stroke patients.

In conclusion, the proposed EMG decoders based on the linear system approach and the nonlinear system approach have a wide range of application in rehabilitation. These approaches showed high potential in controlling robots to support users with safe, smooth, and accurate assistance in rehabilitation.

Publications

The contents of this thesis are based on the following chapters that have been published, accepted, or submitted to peer-reviewed journals and conferences.

Journal Chapters:

1. Yao Huang, Rong Song, Ahmadreza Argha, Andrey V. Savkin, Branko G. Celler, and Steven Su, “Continuous description of human 3D motion intent through switching mechanism,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 1, pp. 277-286, Jan 2020.
2. Yao Huang, Qianqian Yang, Ying Chen, and Rong Song, “Assessment of motor control during three-dimensional movements tracking with position-varying gravity compensation,” *Frontiers in Neuroscience*, vol. 11, no. 253, May 2017.
3. Yao Huang, Rong Song, Ahmadreza Argha, Andrey V. Savkin, Branko G. Celler, and Steven Su, “Human motion intent description based on bumpless switching mechanism for rehabilitation robot,” under review at *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.
4. Yao Huang, Rong Song, Ahmadreza Argha, Andrey V. Savkin, Branko G. Celler, and Steven Su, “EMG-based continuous motion intention description by a mixed-order bumpless decoder for rehabilitation robots control,” ready to submit.
5. Yao Huang, Rong Song, Ahmadreza Argha, Andrey V. Savkin, Branko G. Celler, and Steven Su, “Continuous estimation of motion intention based on EMG signals using a time-variant long short-term memory network,” ready to submit.

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6. Yao Huang, Rong Song, Ahmadreza Argha, Andrey V. Savkin, Branko G. Celler, and Steven Su, “The effect of assistance from an EMG-based control robot on upper limb muscle synergies,” ready to submit.

Book Chapter:

1. Yao Huang, Steven Su, and Rong Song, “Voluntary intention-driven rehabilitation robots for the upper limb,” in *Intelligent Biomechatronics in Neurorehabilitation*, Academic Press, pp. 111-130, 2020.

Conference Chapters:

1. Yao Huang, Rong Song, Wenhui Chen, Hairong Yu, Ahmadreza Argha, Branko G. Celler, and Steven Su, “The effects of different tracking tasks on muscle synergy through visual feedback,” in *Proc. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 417-420, July 2019.
2. Yao Huang, Ying Chen, Jie Niu, and Rong Song, “EMG-Based control for Three-Dimensional upper limb movement assistance using a cable-based upper limb rehabilitation robot,” in *Proc. 2017 International Conference on Intelligent Robotics and Applications*, pp. 273-279, August 2017.

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