

論文 / 著書情報
Article / Book Information

題目(和文)	
Title(English)	The development of content consistent motor imagery brain computer interface for controlling the artificial intelligence robot
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出典(和文)	学位:博士(学術), 学位授与機関:東京工業大学, 報告番号:甲第12259号, 授与年月日:2022年9月22日, 学位の種別:課程博士, 審査員:小池 康晴,中本 高道,金子 寛彦,吉村 奈津江,葭田 貴子
Citation(English)	Degree:Doctor (Academic), Conferring organization: Tokyo Institute of Technology, Report number:甲第12259号, Conferred date:2022/9/22, Degree Type:Course doctor, Examiner:,,,,
学位種別(和文)	博士論文
Category(English)	Doctoral Thesis
種別(和文)	要約
Type(English)	Outline

Tokyo Institute of Technology

School of Engineering

Department of Information and Communication

Engineering

Graduate Major in Human Centered Science and

Biomedical Engineering

**The development of content consistent motor
imagery brain computer interface
for controlling the artificial intelligence
robot**

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Submitted in part fulfillment of the requirements for the

degree of

Doctor of Philosophy (Ph.D.)

Abstract

A technology that allows humans to interact with machines more directly and efficiently would be desirable. Research on brain–computer interfaces (BCIs) provides the possibility for computers to understand human thoughts in a straightforward manner thereby facilitating communication. As a branch of BCI research, motor imagery (MI) can help people suffering from stroke, disabilities, and amyotrophic lateral sclerosis (ALS). To compensate the limitation of execution, an artificial intelligence robotic system which can perfectly implement complex tasks is quite appropriate. To understand the complex instructions generated from brain, a multi classification of right-hand motor imagery based on Electroencephalography(EEG) signal is developed in this study. To improve the BCI robotic techniques, an artificial intelligence robotic system is designed in this study as well.

Acknowledgements

I would like to show greatest appreciation to my advisor Professor Dr.Koike Yasuharu for his guidance and inspiration. He always encourages me to give me hope when I lose my confidence. I could not have imagined the Ph.D study without the support from him.

I would like to express my gratitude to my parents for their wholehearted support and concern for me both spiritually and materially throughout my whole life. I would not reach achievements without them.

I would like to adore my worship to Dr. Jingping Wu. Her companionship encourages me to get through tough times. It must be written in the stars for me to meet her and fall in love with her.

I would like to thank Koike lab staff members, Dr. Natsue Yoshimura, Dr. Hiyoyuki Kambara, Dr. Atsushi Takagi and Dr. Ludovico Minati for teaching me critical thinking when I started considering the research topics and ideas.

I am very grateful for my friends in China, Japan and America, especially my best friend, Dr. Jiaxin Jin. Because of you, I never feel lonely far away from my hometown.

Finally, I would like to thank INOAC scholarship foundation and Tokaichiba Kenyukai. They not only give me the various help in daily life, but also introduce Japanese culture to me with great passion. They give me fond memories of my study abroad life.

Dedication

Dedicated to my parents and my love.

~~~~~ It's a

long long journey,

Till I know where I'm supposed to be.

I leave my home and pursue my dream,

Try to be strong and pretend to be brave.

It's a long long journey,

Till I meet you and I know,

You are the way home to me.

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