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

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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.

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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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