

**ADVANCED NEURAL NETWORK HEAD MOVEMENT CLASSIFICATION FOR
HANDS-FREE CONTROL OF POWERED WHEELCHAIRS**

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This thesis is presented as part of the requirements for the award of the degree of
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Abstract

Assistive technology is increasingly being used to allow people with disabilities to be more engaged in personal, social and vocational activities. However, people with high-level disabilities are still affected by barriers to independence and full inclusion into broader society. The focus of this thesis is to advance the development of a wheelchair control system for highly disabled people, providing a means for satisfying some of the mobility needs of people who have difficulty or are unable to achieve mobility through existing assistive technologies.

A control system allowing hands-free wheelchair control is proposed, advancing from systems previously described in literature. The proposed control system allows the operation of a powered wheelchair by using an artificial neural network (ANN) classifier to recognize head gesture commands. The feasibility of this control system is tested on its ability to correctly recognise command gestures of both able-bodied and disabled people in real-time.

Techniques for improving the ability of the head gesture classifier to recognise gestures performed by people with disabilities are investigated. The effectiveness of these techniques is evaluated for highly disabled people. The effect of empirically selecting an optimal ANN architecture and training algorithm using training data from a general population is considered, as is the marginal benefit of additional training data from such a population. The benefit of adapting the classifier using data from the specific end user is investigated as a means of further improving performance.

While demonstrating the feasibility of the proposed control system, the results presented showed that the performance of the system was lower for people with disabilities than for able-bodied users. It was found that selection of the ANN architecture, training algorithm and training set size all had significant effects of some degree on the ability of the classifier component to recognise command gestures by people with disabilities in real time. It was also found that data from a specific end user to train the ANN can significantly improve classifier performance.

It was found that adapting the classifier ANN using a combination of user specific and generic data could improve the performance of the classifier for that end user while minimising or avoiding any reduction in classifier performance for other people. It was also found that retraining such an ANN with user specific data alone improves the performance of the classifier for that end user but is detrimental to the classification performance for other people.

Notation and terminology

Table 1 Terminology used throughout this thesis

Term	Definition
SCI	Spinal Cord Injury
ANN	Artificial Neural Network
Delta rule	A training algorithm for artificial neural networks, also known as the gradient descent (Hagan 1995) or backpropagation (Haykin 1999) algorithm.
Tetraplegia	Paralysis of all four limbs, also known as quadriplegia
Generic dataset	A set containing recorded gestures or input-output pairs observed from the data provided by a group of people.
Specific dataset	A set containing recorded gestures or input-output pairs observed from the data provided by a single, known person.
PWM	Pulse Width Modulation, a modulation scheme where duty cycle of a square-wave carrier encodes the signal.