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## Human behavioural skills modelling and recognition

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# Human Behavioural Skills Modelling and Recognition

by  
Chao Sun

A dissertation submitted in fulfillment  
of the requirements for the degree of  
Master of Engineering (Research)  
(SECTE)  
in University of Wollongong  
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Supervisor:

Professor Fazel Naghdy,  
Doctor David Stirling,  
Associate Professor Golshah Naghdy.

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## ABSTRACT

Human behaviour can be considered as the ensemble of various activities performed by an individual towards performing a particular task. There are many factors influencing human behaviour including culture, attitudes, emotions, values, ethics, and so on. In this work, the concept of “human behaviour” in the context of human psycho-motor behaviour is studied.

This work is primarily concerned with the development of a system to learn, distinguish and recognise various pre-defined human behavioural tasks. As an initial constraint, the challenging goal, subject to the limitation of hardware, is to model various human behaviours with only one integrated inertial sensor. The motions are captured with the sensor and recorded as streams of multi-dimensional sensory data, which are subsequently analysed into certain patterns. Since only one point on the human body can be measured with that sensor at a time, there are not sufficient motion data to enable the generation of new synthetic behaviours (which might be possible with multiple sensors). It is not really possible to develop a comprehensive model of complex behaviours under this condition. Thus, this work has focussed on building a system to model the behaviour of a specific part of the human body, and in turn to recognise and compare these behaviours.

The experimental rig consists of an inertial sensor mounted on the subject providing kinematics data in real-time. Through this sensor, the behavioural motions are transformed into continuous streams of signals including Euler angles

and accelerations in three spatial dimensions. Unsupervised machine learning algorithms and other techniques are implemented to analyse and build models of human behaviours in this work. An intrinsic classification algorithm called MML (Minimum Message Length encoding), and a popular unsupervised fuzzy clustering algorithm FCM (Fuzzy c-Means) are used to segment the complex data streams respectively, formulating inherent models of the dynamic modes they represent. Subsequent representation and analysis including FSM (Finite State Machines), DTW (Dynamic Time Warping), Kullback-Leibler divergence and Smith-Waterman sequence alignment have proved quite effective in distinguishing between behavioural characteristics that persist across a variety of tasks and multiple candidates.

The hypothesis pursued in the thesis has been validated based on two machine learning algorithms for unsupervised learning namely MML and FCM. Each of these methods is capable of producing a range of primitives from the motion training data. However, the outcomes of regular expression and Dynamic Time Warping analysis results indicate that MML provides better results compared with the FCM algorithm in terms of identifying behaviours.

Dedicate to My Family

## DECLARATION

I, Chao Sun, declare that this thesis, submitted in fulfilment of the requirement for the award of Master of Engineering, in the School of Electrical, Computer and Telecommunications Engineering, Faculty of Infomatics, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. No part of this document has been submitted for qualifications at any other academic institution.

(Signature)

**Chao Sun**

31/Oct/2007



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## **PUBLICATIONS**

- [1]. Sun, C.; Naghdy, F. & Stirling, D., "Application of MML to Motor Skills Acquisition", International Conference on Computational Intelligence for Modelling, Control and Automation - CIMCA06, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce - IAWTIC06, Nov. 2006.
- [2]. Sun, C.; Stirling, D. & Naghdy, F., "Segmentation of Inertial Motion Data", Australasian Conference on Robotics and Automation, ACRA'2006, Dec. 2006.
- [3]. Sun, C.; Stirling, D. & Naghdy, F., "Skill acquisition through Data mining of Inertial Signals", the 5th Workshop of the Internet Telecommunications and Signal Processing, WITSP'2006, Dec. 2006.

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