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**Time Series Classification for Analysing the
Impact of Architectural Design on
Pedestrian Spatial Behaviour**

by
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Thesis submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy in Computer Science

June, 2012

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Acknowledgments

I consider myself very fortunate to have had the opportunity to live and study in Newcastle. With its natural beauty, Newcastle provides an ideal setting for academic excellence. Not only I have received world-class training in modern machine learning, I have had the pleasure of forming many close friendships and exciting collaborations amongst the numerous highly esteemed academics I have worked with.

As is ever so common in research today, progress is rarely made without collaboration amongst colleagues from various areas within the local and distant academic community. I would like to take this opportunity to thank all those who have contributed to the fields of scientific endeavour perused throughout this thesis. Not only those mentioned below but the countless workers that dedicate their talents to this respectively important field.

First and foremost, I would like to express my deepest gratitude to Associate Professor Stephan Chalup for granting me this opportunity. He has continuously instilled confidence in me and has truly believed in my abilities. Under his guidance, I have been able to realise a dream and life long academic passion. His extensive experience has been invaluable and his level of patience, not only admirable but critical to my success.

Professor Michael Ostwald has provided uniquely insightful suggestions and I appreciate the experience in the architectural application domain that he has facilitated. His inspirational personality and extraordinary intelligence is priceless in guiding students. The level of attention and genuine care he expresses is remarkable.

I would like to thank to Doctor Eamonn Keogh, and Doctor A. Frank for providing very useful machine learning data sets in UCR and UCI repositories. In addition, I would like to thank Doctor Sepp Hochreiter and Doctor Klaus Obermayer for introducing P-SVMs. To all paper reviewers who have provided outstanding feedback.

Newcastle City Council and Screen Hunter Central Coast have been very helpful in supporting the Human Ethics approval process. I gratefully acknowledge Roseanne Linich for providing ESL support during my doctorate studies.

This work would not have been possible without the financial support provided by the Australian Research Council - “Modelling and Predicting Patterns of Pedestrian Movement”. Grant No. DP1092679.

On a personal note, I express my appreciation to my colleagues in the Interdisciplinary Machine Learning Research Group, for their stimulating discussion, ideas, encouragement, expertise and genuinely keen approach to team work. To my friends for being understanding of my commitment during this period, especially as I complete this thesis by writing this acknowledgement. Of special note Doctor Houman Ebrahimi, my dear friend and imminent business co-founder.

Being away from family has not been easy but this endeavour has not only been possible through focus and dedication but it has taken years of preparation and ongoing support from my dear family. My father Hassan Jalalian, my mother Mansure Azam Feizmanesh and my brother Ashkan Jalalian. They have been amazing in bridging the immense physical distance that separates us. Their supports and prayers have truly been invaluable.

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Abstract

Pedestrian spatial behaviour is defined as the pedestrians' reaction to their immediate surroundings. Analysis of changes in this behaviour due to alternation in the environmental settings is an important facet of architectural and urban design. To measure the changes, human body dynamics, such as head position, gaze direction, movement direction, speed of movement, and trajectory can be employed. In this research the main purpose is to support architects and urban designers to better assess the impact of the spatial environment on the pedestrian's behaviour in planned urban spaces. To this end, an analysis system is proposed to learn the patterns of behaviour observed in a simulated and real-world architectural space.

The simulated environment is generated using the proposed pedestrian and urban models. The models provide important behavioural characteristics in a multi-agent-based simulation system. They support complex spatial interactions between agents and their environment, including agent-to-agent interactions, different spatial desires, and interpersonal distance. The simulated environment can be automatically generated using scanned line drawings of two-dimensional street maps or public spaces. In the simulation model, a variety of scenarios can be defined and modified by altering different parameters. Using the example of Wheeler Place in Newcastle (Australia), the experiments demonstrate how pedestrian behavioural characteristics can depend on selected abstract features in urban spaces. The characteristics are used in the analysis system to distinguish between different patterns of spatial behaviour.

The analysis system consists of a proposed technique for sequential data classification where each data object may have different lengths. The new technique, called GDTW-P-SVMs, is a maximum margin method for the construction of classifiers with variable-length input series. It employs potential support vector machines (P-SVMs) and dynamic time warping (DTW) to waive the fixed-length restriction of feature vectors in standard support vector machines (SVMs). The new technique elaborates on the P-SVM kernel function, by utilising DTW to provide an elastic distance measure for the kernel function. Benchmarks for classification are performed with several real-world data

sets from the UCR Time Series Classification/Clustering page, GeoLife trajectory data set, and UCI Machine Learning Repository. The data sets include data with both variable and fixed-length input series. The results show that the new method performs significantly better than the benchmarked standard classification methods.

To learn patterns of spatial behaviour the proposed classification technique is employed with simulated and real-world characteristics. The characteristics are collected from Wheeler Place using the proposed simulation software and pedestrian tracking system. GDTW-P-SVMs classify patterns of behaviour using the whole sequence of data series as a single input to increase the classification performance. As a result, they can provide the highest classification accuracy using the simulated and real-world data sets, when compared with the other existing methods.

Keywords: Spatial Behaviour Analysis, Trajectory Data Analysis, Support Vector Machines, Dynamic Time Warping

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