

Multi-Attribute Based Data Modeling for Network Applications  
in Cyber-Physical Environments

by

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Doctor of Philosophy in Software Engineering

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Faculty of Science and Technology

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## Abstract

This thesis is devoted to solve problems faced in developing network applications in cyber-physical environments using multi-attribute based data modeling and methodology.

Recent advancements in embedded systems, sensors and wireless communication technologies have led to the development of Cyber-Physical Systems (CPSs). As an integral component of CPSs, Wireless Sensor Networks (WSNs) offer great potential for developing the new network applications. However, due to the complicity of the cyber-physical environments, there exist many influential factors/attributes that need to be considered in these new applications. Comprehensive consideration and utilization of multiple influential factors/attributes to make better decisions or seek the optimal solution has become an essential problem.

To address this issue, we first summarize the multi-factor/multi-attribute problems into two types: the multi-attribute ranking problem and the multi-attribute optimization problem. And then, we focus on these two types of problems in networked cyber-physical environments, and study the multi-attribute decision-making (MADM) and learning approaches in three network applications: the traffic information collection and vehicle navigation in Intelligent Transportation Systems (ITSs), and data clustering in the large, dynamic distributed networks.

Firstly, the traffic-monitoring system is studied. A flexible urban traffic information collection framework based on WSNs is presented and verified. A novel user-customizable data-centric routing scheme is proposed for traffic information delivery, in which multiple routing-related information is considered for decision-making to



meet different user requirements. Simulations show the good performance of the proposed routing scheme compared with other traditional ones on real-world urban traffic networks.

Secondly, the vehicle navigation system is studied in urban traffic networks. A novel WSN-based real-time vehicle navigation algorithm is proposed. The hybrid MADM method is presented for the real-time navigation decision-making. A new general distance metric is defined for the processing of both exact and fuzzy data. Simulations show the suitability and efficiency of the proposed algorithm.

Finally, attribute-weighted distributed data clustering is studied and a novel collaborative clustering algorithm based on distributed Peer-to-Peer (P2P) networks is proposed. The attribute-weight-entropy regularization technique is used to obtain good clustering results and yield the optimal attribute weights. The kernel method is utilized in the proposed clustering algorithm to meet the needs of ‘non-spherical’ shaped data clustering. Experiments on synthetic and real-world datasets demonstrate the efficiency and superiority of the proposed algorithm.

## Declaration

I declare that the thesis here submitted is original except for the source materials explicitly acknowledged and that this thesis as a whole, or any part of this thesis has not been previously submitted for the same degree or for a different degree.

I also acknowledge that I have read and understood the Rules on Handling Student Academic Dishonesty and the Regulations of the Student Discipline of the University of Macau.

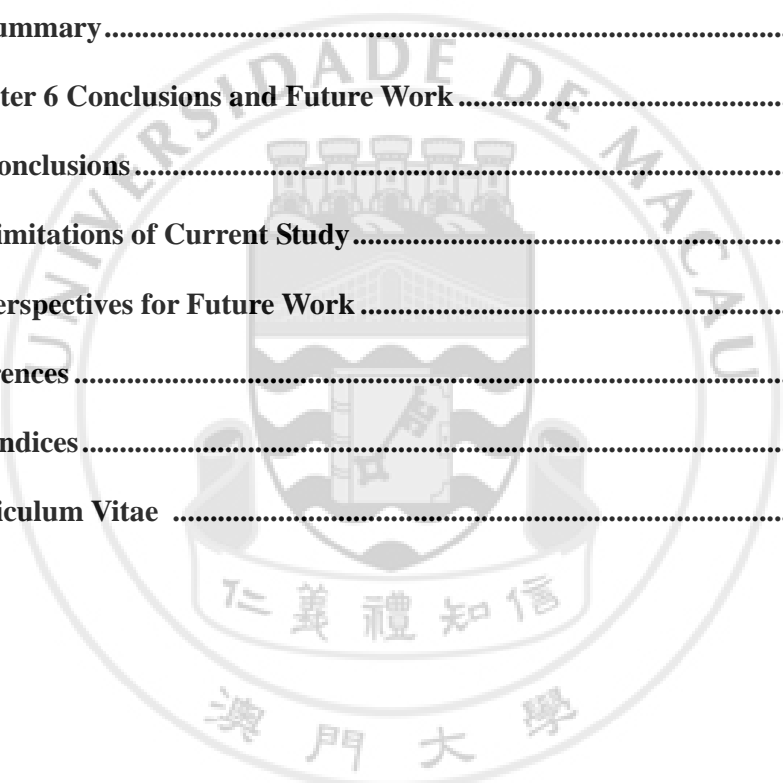


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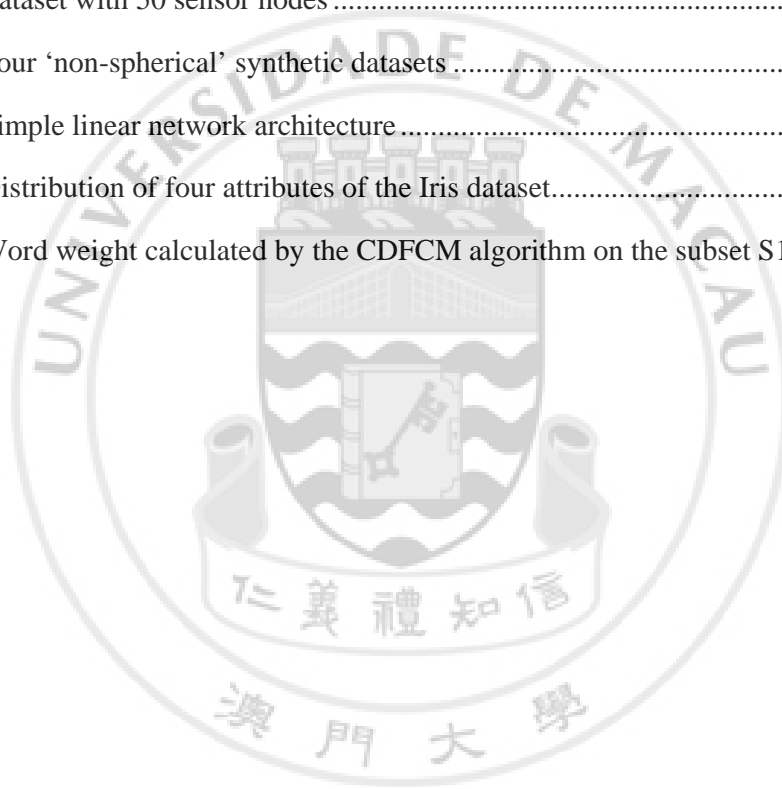
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## List of Abbreviations

ACR: Average Classification Rate

ADT: Average Delay Time

AHP: Analytic Hierarchy Process

AIN: Average Iteration Number

ANMI: Average Normalized Mutual Information

ARE: Average Residual Energy

ATE: Average Transmission Energy

ATEC: Average Transmission Energy Consumption

CDFCM: Collaborative Distributed Fuzzy C-Means

CDT-R: Cost and Delay Time combined Routing

CPSs: Cyber-Physical Systems

C-R: Cost-based Routing

CR: Classification Rate

CRE-R: Cost and Residual Energy combined Routing

FCM: Fuzzy C-Means

GPS: Global Position System

IN: Iteration Number

ITSS: Intelligent Transportation Systems

KCDFCM: Kernel-based Collaborative Distributed Fuzzy C-Means

KFCM: Kernel-based Fuzzy C-Means

L-R: Level-based Routing

MADM: Multi-Attribute Decision Making

MADM-R: Multi-Attribute Decision Making based Routing

MAUT: Multi-Attribute Utility Theory

MEI: Maximum Entropy Inference

MRE: Minimum Residual Energy

MTEC: Maximum Transmission Energy Consumption

MV: Mean of Velocity

NL: Network Lifetime

NMI: Normalized Mutual Information

P2P: Peer-to-Peer

SDRE: Standard Deviation of Residual Energy

SUMO: Simulation of Urban Mobility

TD: Travel Distance

TEC: Transmission Energy Consumption

TIC: Traffic Information Center

TOPSIS: Technique for Order Preference by Similarity to Ideal Solution

TT: Travel Time

UCI: University of California Irvine

VANETs: Vehicular *Ad Hoc* Networks

WSNs: Wireless Sensor Networks

