

**Case-based Expert System using Wavelet Packet
Transform and Kernel-based Feature
Manipulation for Engine Spark Ignition Diagnosis**

by

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**Faculty of Science and Technology
University of Macau**

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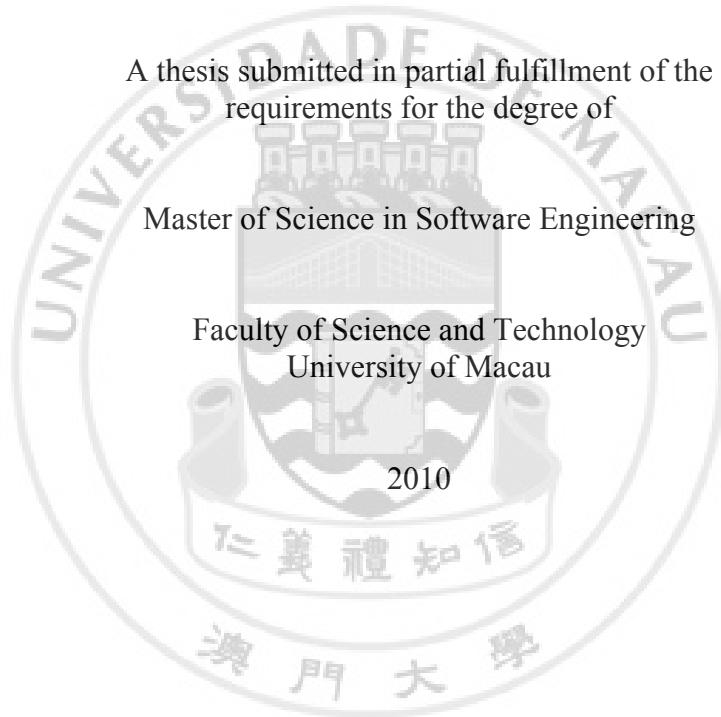
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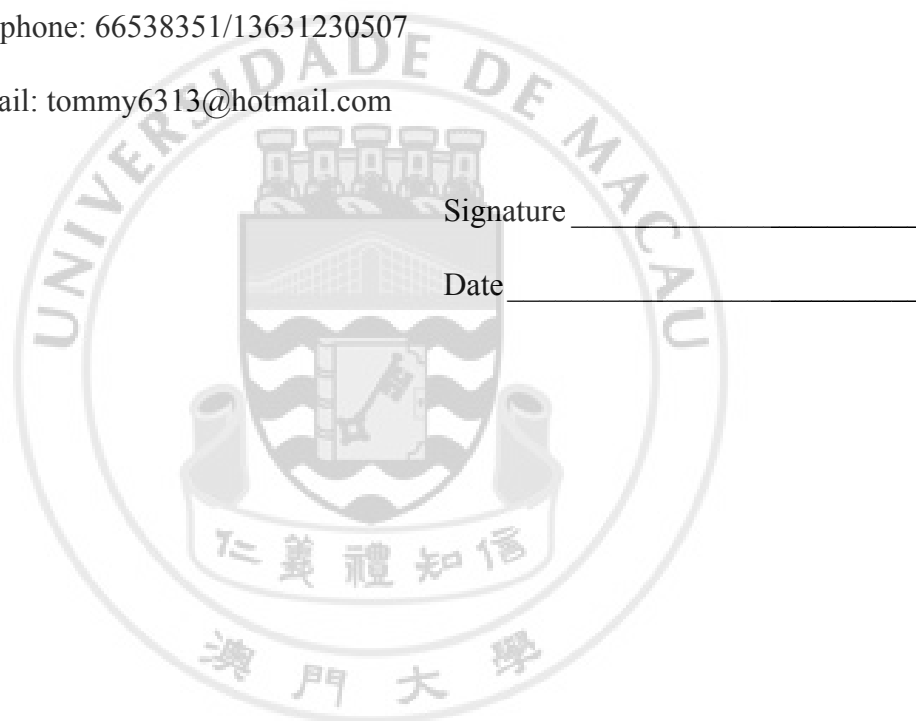
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Abstract

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With the development of modern technology, modern vehicles adopt electronic control system for injection and ignition. In traditional way, whenever there is any fault in an automotive engine, an automotive mechanic usually performs a diagnosis in the ignition system of the engine to check any exceptional symptoms, based on specific domain knowledge (domain features of an ignition signal). In this paper, case-based reasoning (CBR) approach is presented to help solve human diagnosis problem based on not only the domain features, but also the extracted features of signals captured using a computer-linked automotive scope meter. The advantage of CBR expert system is that multiple possible diagnoses can be provided to the user, instead of a single most probable diagnosis provided by traditional network-based models such as multi-layer perceptions (MLP) and support vector machine (SVM). In addition, CBR can overcome the problem of incremental and decremental model update compared to MLP and SVM. CBR is effective but mostly inefficient in time

especially for high dimensional domains because every instance in a case library must be compared during reasoning. To overcome this inefficiency, a combination of preprocessing methods was employed, such as wavelet packet transform (WPT), kernel principal component analysis (KPCA) and kernel k-means (KKM). Considering the ignition signals captured by scope meter are very similar, WPT was proposed for feature extraction so that the ignition signals can be compared with the extracted features. However, there exist many redundant points in the extracted features which will degrade the diagnosis performance. Therefore, KPCA was employed to perform dimension reduction. In addition, the number of cases in case library can be controlled through clustering and KKM was adopted for this purpose. Several methods have been used for diagnosis including MLP, SVM and CBR. From the experimental results, CBR generates high accuracy and fits better the requirements of an expert system.

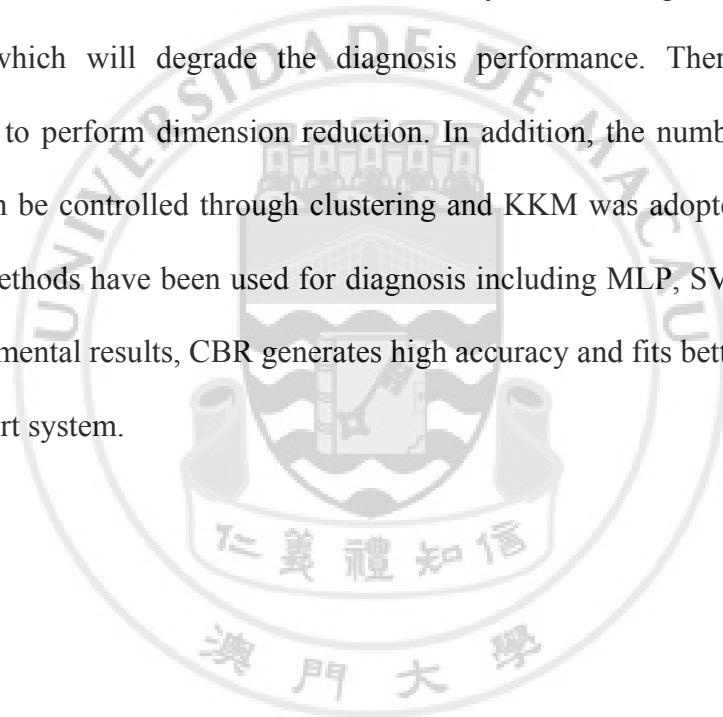


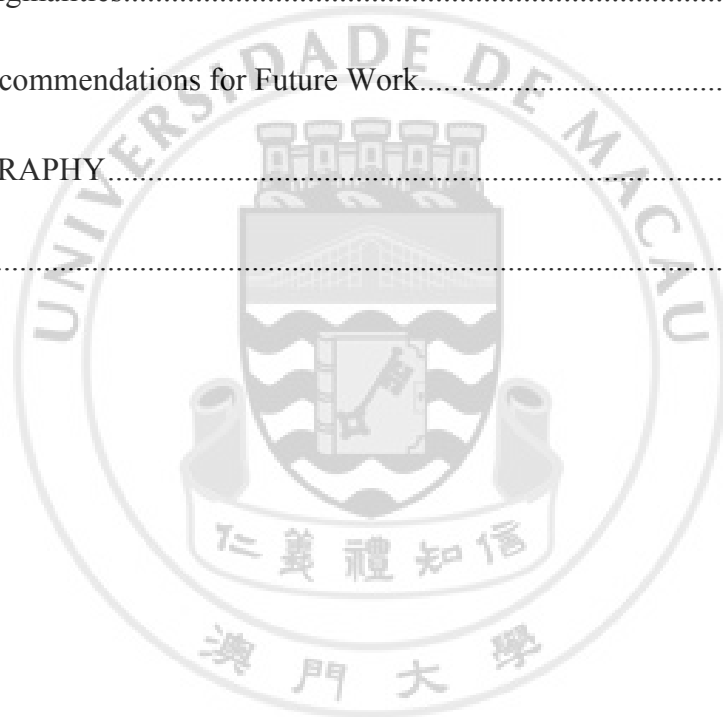
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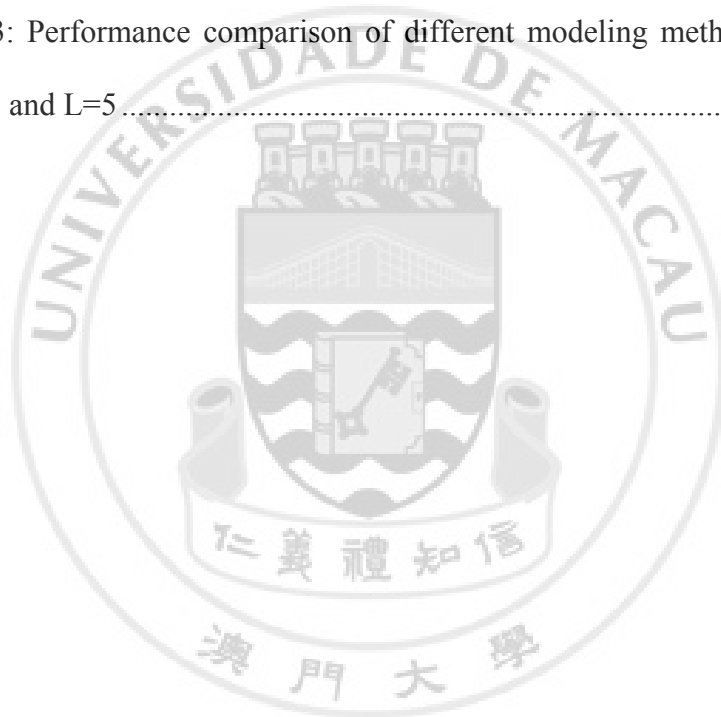


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LIST OF ABBREVIATIONS

EPA: Environmental Protection Agency

HC: Hydro Carbon

CBR: Case-Based Reasoning

MLP: Multi-Layer Perceptions

SVM: Support Vector Machine

WT: Wavelet Transforms

DWT: Discrete Wavelet Transform

WPT: Wavelet Packet Transform

KPCA: Kernel Principal Component Analysis

KKM: Kernel K-Means

AEM: Abnormal Event Management

SDG: Signed Directed Graph

QSIM: Qualitative Simulation

QPT: Qualitative Process Theory

QTA: Qualitative trend analysis

PCA: Principal Component Analysis

PLS: Partial Least Squares

IDE: Integrated Development Environment

RBF: Radial Basis Function

