Simultaneous Fault Diagnosis of Automotive Engine Ignition Systems using Pairwise Coupled Relevance Vector Machine, Extracted Pattern Features and Decision Threshold Optimization

by

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Abstract

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Whenever there is any fault in an automotive engine ignition system or change of engine conditions, a mechanic can analyze the engine ignition patterns to identify the engine fault according to both the specific domain knowledge and the shape features of the patterns. One of the challenges in ignition system diagnosis is that more than one fault may appear at a time. This kind of problem refers to simultaneous fault diagnosis. Another challenge is the acquisition of large amount of costly simultaneous-fault ignition patterns for constructing the diagnostic system because the number of the training patterns depends on the combination of different single faults. The above problems could be resolved by the proposed framework combining feature extraction, probabilistic classification, and decision threshold optimization. For feature extraction, the thesis proposes to use wavelet packet transform and principal component analysis together with domain knowledge. With the proposed framework, the features of the single faults in a simultaneous-fault pattern are extracted and then detected using a new probabilistic classifier namely pairwise coupling relevance vector machine, which is trained with single-fault patterns only. Therefore, the training dataset of simultaneous-fault patterns is not necessary. Experimental results show that the proposed

framework performs well for both single-fault and simultaneous-fault diagnoses, and is superior to the existing approach.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Number *Page*

LIST OF ABBREVIATIONS

$\mathbf{A}$: diagonal matrix of hyperparameters

a: end point of burning time

$\mathbf{B}$: diagonal matrix in RVM

$\mathrm{B}f_j(.)$: jth binary classifier

C_i: ith probabilistic classifier

$\mathrm{C}_i(\mathbf{f})$: probability of $\mathbf{f}$ belonging to the ith label

C_{ij}: pairwise classifier

$\mathrm{C}_{ij}(\mathbf{f})$: pairwise probability of $\mathbf{f}$ belonging to the ith label against the jth label

c_1: cognitive parameter of PSO

c_2: social parameter of PSO

D: sample dataset

d: number of labels (faults)

e_j: jth eigen value

e_j': jth normalized eigen value

$\mathbf{F}$: set of feature vectors

$\mathbf{F}'$: set of feature vectors created by WPT and PCA

F_1: firing voltage

F_2: burn time

F_3: average spark voltage of spark line

F_{me}: F-measure

$\mathbf{f}$: feature vector

$\mathbf{f}'$: feature vector created by WPT and PCA

$\mathbf{f}_h$: hth feature vector

f_{class}: probabilistic classifier

H: PCA transformation matrix

$\mathbf{h}_j$: jth eigen vector

J: decomposition level of WPT

K(.): kernel function in RVM

L_P: length of ignition pattern (i.e. number of data point in ignition pattern)

l: true label vector

$\mathbf{l}_i$: ith true label vector

l_i: ith label in **l**

l_{ig}: gth label in $\mathbf{l}_i$

l_i^j : ith label in the jth test data

N: number of training data

N_D: number of cases in sample dataset

N_T: number of test data

n_{ij}: number of training data with the i^{th} and j^{th} labels

$P(l_j|\mathbf{f})$: probability of **f** belonging to l_j

P(.): probability

s: input dimension of classifier to be evaluated

t: set of faulty labels in training dataset

t_n: faulty label of the nth training case

TEST: original test dataset

$TEST_1$: single fault cases in test dataset

$TEST_s$: simultaneous fault cases in test dataset

TEST_F: test dataset after feature extraction

TRAIN: original training dataset

TRAIN_F: training dataset after feature extraction

V: set of coefficient vectors

VALID: original validation dataset

VALID_F: validation dataset after feature extraction

v: coefficient vector

w: optimal vector in RVM

w_n: nth optimal parameter in RVM

$\mathbf{w}_{MP}$: most probable weight vector in RVM

w_c: inertial weight of PSO

WPT(.): wavelet packet transform function

X: set of ignition pattern vectors

x: unseen ignition pattern

x_i: ith data point in **x**

y: predicted label vector

y_i: ith predicted label

y_i^j : ith predicted label in the jth test data

$z(\mathbf{f})$: predicted decision

$\boldsymbol{\alpha}$: hyperparameter vector of RVM

α_n: nth hyperparameter of RVM

ε: decision threshold

ε_k: kth tentative threshold produced in optimization process

ε_{opt}: optimized threshold

$\theta(.)$: decision function of binarization approach

π: precision

$\boldsymbol{\rho}$: probability vector

ρ_i: probability of the *i*th label

ρ_{ij}: pairwise probability of the *i*th label against the *j*th label

$\mathbf{\Sigma}$: covariance matrix in RVM

$\mathbf{\Sigma}_{ii}$: *i*th diagonal element of covariance matrix $\mathbf{\Sigma}$

σ(.): logistic sigmoid function

τ: recall

Є: initial population

$\mathbf{\Phi}$: design matrix in RVM

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