IDENTIFICATION OF GROUND VEHICLE’S AERODYNAMIC DERIVATIVES USING NEURAL NETWORK

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To my beloved mother, father, sisters and brothers

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ABSTRACT

Stability of a ground vehicle is dependent on its aerodynamic characteristics when encountered by sudden crosswind disturbances. Aerodynamic side force and yaw moment have been identified as the main influence on the sensitivity of a vehicle towards crosswind, which is largely shape related. A reliable identification technique is a prerequisite to estimate the aerodynamic side force and the yaw moment. One of the recent techniques in wind-tunnel testing is the use of a pure yawing motion test rig to simulate the transient behavior of a simple vehicle model in crosswind condition. Adapting the stiffness and damping approach, the lateral aerodynamic derivatives are evaluated from the identified system's frequency and damping of a pure yawing motion. This research explores the alternative identification technique apart from the conventional method of using a spectral density plot to identify the system's frequency and the logarithmic decrement of peak amplitude for estimating the system's damping from a recorded impulse response data. The present study aims to design a multilayer feedforward neural network to carry out the estimation of natural frequency and damping ratio trained with the Bayesian Regularization training algorithm. The network properties studied are necessary to give insight on the optimum network architecture, the suitable input representation and the effect of noise. The possibility of using principal component analysis technique for reducing the network input dimension has also been explored. The results show that the neural network is able to approximate the natural frequency and the damping ratio of an impulse response data and also the ability of the network to handle noisy input data. The application of principal component analysis technique has been shown to reduce the network input dimension while maintaining good estimation results and shortening the network training period. This study demonstrates that the identification of the frequency and the damping of the system can be done using neural network and can be applied to any other similar systems.

ABSTRAK

Kestabilan kenderaan darat bergantung kepada ciri aerodinamiknya apabila berhadapan dengan gangguan angin lintang mengejut. Daya sisi aerodinamik dan momen rewang aerodinamik adalah pengaruh utama yang menentukan kepekaan kenderaan terhadap angin lintang dan nilainya berkait dengan bentuk kenderaan. Satu teknik yang boleh diharap bagi mengenalpasti nilai daya dan momen aerodinamik merupakan satu prasyarat. Salah satu teknik terkini dalam ujian terowong angin adalah penggunaan rig pergerakan rewang tulen untuk menyelakukan kelakuan fana model ringkas kenderaan dalam keadaan angin lintang. Menggunakan pendekatan kekakuan dan peredaman, nilai terbitan aerodinamik sisi diperolehi daripada nilai kekakuan dan redaman sistem tersebut. Penyelidikan ini meneroka teknik pengenalpastian alternatif selain daripada teknik lazim yang mana nilai kekakuan dikenalpasti menerusi penggunaan plot ketumpatan spektral dan nilai redaman diperolehi daripada teknik penyusutan logaritma amplitud puncak. Kaedah pengenalpastian ini adalah berdasarkan sambutan dedenyut sistem tersebut yang telah direkodkan. Kajian ini bertujuan untuk menghasilkan rangkaian neural suap depan berbilang lapis untuk mengenalpasti nilai frekuensi tabii dan nisbah redaman yang dilatih dengan algoritma Penyusunan Semula Bayesian. Sifat rangkaian neural yang dikaji adalah perlu untuk memberi gambaran bagi menghasilkan seni bina rangkaian yang optimum, perwakilan masukan yang sesuai, dan kesan hinggar. Kajian ini juga mengkaji kemungkinan penggunaan teknik analisis komponen utama bagi mengurangkan dimensi masukan rangkaian neural. Hasil kajian menunjukkan bahawa rangkaian neural boleh menganggarkan nilai frekuensi tabii dan nisbah redaman sambutan dedenyut dan ia juga boleh mengendalikan data masukan yang dipengaruhi oleh hingar. Penggunaan analisis komponen utama pula boleh mengurangkan dimensi masukan rangkaian neural sementara mengekalkan nilai anggaran yang baik dan memendekkan tempoh latihan. Kajian ini telah menunjukkan kaedah pengenalpastian frekuensi dan redaman sesuatu sistem oleh rangkaian neural dan ia boleh diaplikasikan kepada sistem lain yang setara.

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LIST OF SYMBOLS

A	-	Frontal model area
a	-	Neuron output
b	-	Biases
C_a	-	Aerodynamic damping
cg	-	Center of gravity
Cn_β	-	Aerodynamic yaw moment derivatives
Cn_r	-	Aerodynamic yaw damping derivatives
cp	-	Center of pressure
Cr	-	Mechanical damping
Cy	-	Side force coefficient
Cy_β	-	Aerodynamic side force stiffness derivatives
Cy_r	-	Aerodynamic side force damping derivatives
D	-	Aerodynamic Drag
F_{reg}	-	Regularization objective function
F	-	Force
F_w	-	Sum squares weight
f	-	Neuron activation function
f	-	Frequency
f_d	-	Damped frequency
$\mathbf{H}$	-	Hessian matrix
$\mathbf{I}$	-	Identity matrix
I_{zz}	-	Model rig yaw moment of inertia
$\mathbf{J}$	-	Jacobian matrix
K_a	-	Aerodynamic stiffness
K_r	-	Mechanical stiffness

K_s	-	Spring linear stiffness
k_m	-	Reduced frequency
L	-	Aerodynamic Lift
l	-	Characteristic model length
l_{cp}	-	Distance between *cp* and *cg*
M	-	Aerodynamic Pitching moment
N, N_a	-	Aerodynamic yaw moment
N_β	-	Aerodynamic yaw moment stiffness
$\hat{N}_\beta$	-	Normalized aerodynamic yaw moment stiffness
N_r	-	Aerodynamic yaw moment damping
$\hat{N}_r$	-	Normalized aerodynamic yaw moment damping
n	-	Induced local field
R	-	Aerodynamic Rolling moment
Re	-	Reynolds number
r	-	Yaw rate
T	-	Torque
t	-	Time
$t_{1/2}$	-	Time to half amplitude
U	-	Freestream air velocity
V	-	Air velocity
V	-	Neuron performance function
w	-	Weights
Y	-	Aerodynamic Side force
Y_β	-	Aerodynamic side force stiffness
α, β	-	Regularization parameter
β	-	Yaw angle
$\dot{\beta}$	-	Yaw rate
$\ddot{\beta}$	-	Yaw acceleration
β_o	-	Initial yaw angle

δ	-	Sensitivity of network performance index to changes in the net input
γ	-	Effective number of parameter
λ	-	Eigenvalue
μ, ϕ	-	Marquardt parameter
ρ	-	Air density
ω_d	-	Damped frequency
ω_n	-	Natural frequency
ζ	-	Damping ratio

LIST OF ABBREVIATIONS

BP	-	Backpropagation
MLNN	-	Multilayer neural network
MSE	-	Mean square error
PC	-	Principal component
PCA	-	Principal component analysis
PSD	-	Power spectral density
PSNR	-	Peak signal-to-noise ratio
rms	-	Root mean square
SSE	-	Sum square error

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Crosswind stability is an important area of study in vehicle aerodynamic design for it leads to safety issues. The main concern in aerodynamic design for years has been concentrated on reducing the drag for fuel efficiency. Later on, it was found that the streamlined vehicle shapes are sensitive to crosswind disturbance. The styling trend towards rounder shapes especially at the rear of the vehicles and a continuing reduction in aerodynamic drags are suspected to contribute to the crosswind sensitivity (Howell, 1993).

The theoretical and computational fluid dynamic methods have yet to prove their reliability in investigating the vehicle behavior in crosswind disturbance and ground vehicle aerodynamicist resorts to the experimental techniques where wind-tunnel testing has been widely used to simulate the transient condition. The primary motivation to this work is to design an alternative parameter identification technique to estimate ground vehicle's aerodynamic derivatives. One of the early uses of parameter estimation was to validate wind tunnel or analytical predictions of aircraft stability and control derivatives (Ming-Der, 1990). Quantitative analysis of ground vehicle stability and its handling qualities make direct use of these parameter estimates. Thus, it is important to have a reliable parameter identification technique for these analyses.

1.2 Problem Statement

The oscillating test rig for wind tunnel testing that has been developed by Mansor (2006) managed to capture the transient response of a simple automotive body type in crosswind disturbances. The following mathematical analysis of the oscillating test rig model enables the determination of aerodynamic derivatives from the system's stiffness and damping which are governed by the natural frequency and damping ratio and was identified in a conventional manner. Conventional method uses an indirect manner of identifying the aerodynamic derivatives where the damping ratio is calculated from the time to half amplitude and frequency is obtained from peak-picking method based on power spectral density calculation.

In the current work, a multilayer neural network was developed to carry out the function approximation task where the natural frequency and damping ratio is approximated based on the recorded impulse time response data. The study investigates the effectiveness of neural network with respect to input representation to the network, the network architecture, the training samples distribution and size, and the application of principal component analysis in reducing the size of the network input dimension. The estimated natural frequency and damping ratio from the designed network is used to calculate the aerodynamic derivatives and the results were compared with the derivatives retrieved through conventional identification process. To validate both techniques, impulse responses were generated from the model systems transfer function and the generated data were compared with the response actually recorded during wind tunnel test.

1.3 Research Objectives

The first objective of this research work is to design an alternative identification scheme for identification of ground vehicle's aerodynamic derivatives. The work proposes on the use of an artificial neural network that can identify the natural frequency and damping ratio given the impulse response of the automotive body recorded from the oscillating test rig. Secondly, this neural network approach is aimed to provide an alternative identification technique in identifying the natural frequency and damping ratio. The performance from both techniques; conventional and neural network, are compared. Through a modern computational approach, the steps in the identification process in estimating the modal parameters are tried to be reduced.

The properties of the network had been studied to construct the optimum design of neural network that can give a good estimation of damping ratio and natural frequency. In this identification work, the aerodynamic damping that acted on the bluff body is considerably low and it is crucial that the designed network should be able to give good estimation values. In addition, the network should be able to generalize well since all the response measured during the wind tunnel test are of arbitrary pair of natural frequency and damping ratio that have not been encountered by the network during the training process.

To optimize the network size which is proportional to the number of input nodes, the proper input representation to the network had been investigated. This work explores on the possibility of introducing the application of principal component analysis in reducing the number of input nodes to the network. The well used technique in the pattern recognition using the neural network were extended to the function approximation application since this identification process was conducted offline based on the past recorded time response.

1.4 Research Methodology

The estimation of the aerodynamic derivatives was based on the time response data recorded during the dynamic wind tunnel test conducted by Mansor (2006). The impulse response was recorded within the linear range of oscillation (below ±20°) and within the frequency range of influence to the vehicle's crosswind sensitivity given by the reduced frequency of 0.09 - 0.9. The estimation was based on the response amplitude range from 10° to 1° as the range has lesser significant effect from the initial release and the influence of noise.

The estimation of the aerodynamic derivatives are based on the identification of the frequency and damping of the measured response. The identification process was carried out with two identification tools; the conventional technique and the multilayer neural network as in Figure 1.1. These two identification tools were used to identify the natural frequency and damping ratio from the measured impulse response data. The aerodynamic derivatives were calculated using the identified parameters and the results from both approaches were compared.

For the neural network approach, a multilayer feedforward neural network (MLNN) was first trained using the training data that were generated from the standard second order systems transfer function. The neural network was trained in an inverse system method using the Bayesian regularization training algorithm. Two methods of input representation were introduced. The first representation is in the form of standard plot of a second order system while the second representation consists of the whole impulse response input to the network. In optimizing the size of input nodes in the second representation, principal component analysis was used. The neural network properties were investigated before the proper network architecture was selected. The network was trained in an iterative process until the network output coincides with the targeted output. Figure 1.2 shows the training process for the two input representation method.

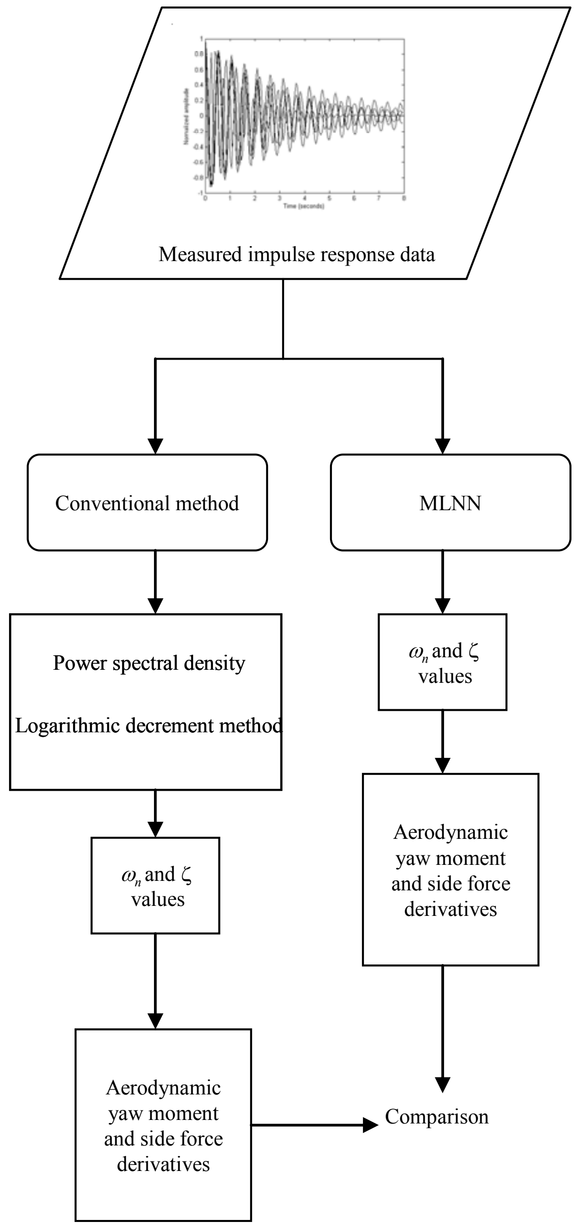

Figure 1.1 Overall research process

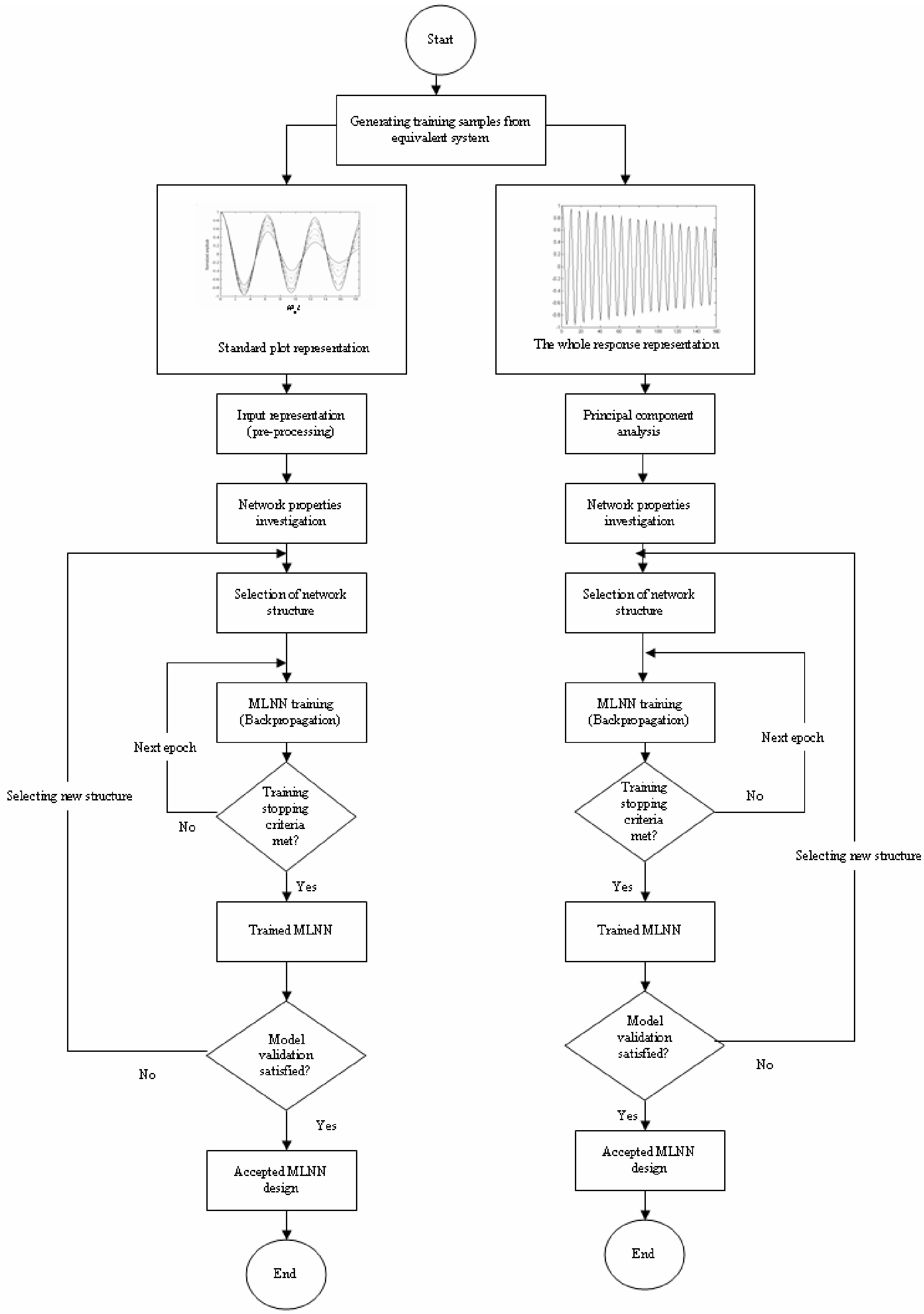

Figure 1.2 Training process of the MLNN

1.5 Scope of work

The current research work is limited to the following:

(i) Using available experimental data. The data was generated from a free oscillation test using an oscillating test rig to capture the transient behavior of a simple model in crosswind.

(ii) The identification of yaw moment and side force derivatives for ground vehicle in crosswind. The derivatives value gives the rate of change of aerodynamic force or moment acting on the body with respect to yaw angle.

(iii) Identification based on damped response of a second order system given that the system is of pure yawing motion of a single degree of freedom system.

(iv) The damping ratio range is between 0.001-0.1 and natural frequency ranges from 2.5-26.5 rad/s.

(v) Using a multilayer feedforward neural network.

(vi) Training algorithm: Bayesian Regularization.

1.6 Organization of the thesis

This thesis is divided into 6 main chapters. The introduction in this chapter is aimed to give some background on the research work. The purpose of the study and the methodology used to achieve the research objective is described and the thesis content is overviewed. The previous research work related to the study is presented in Chapter 2.

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