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Modelling of a Flexible Manoeuvring System Using ANFIS Techniques

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Abstract— *The increased utilization of flexible structure systems, such as flexible manipulators and flexible aircraft in various applications, has been motivated by the requirements of industrial automation in recent years. Robust optimal control of flexible structures with active feedback techniques requires accurate models of the base structure, and knowledge of uncertainties of these models. Such information may not be easy to acquire for certain systems. An adaptive Neuro-Fuzzy inference Systems (ANFIS) use the learning ability of neural networks to adjust the membership function parameters in a fuzzy inference system. Hence, modelling using ANFIS is preferred in such applications. This paper discusses modelling of a nonlinear flexible system namely a twin rotor multi-input multi-output system using ANFIS techniques. Pitch and yaw motions are modelled and tested by model validation techniques. The obtained results indicate that ANFIS modelling is powerful to facilitate modelling of complex systems associated with nonlinearity and uncertainty.*

Keywords – ANFIS; flexible systems; model validation

I. INTRODUCTION

Flexible structures are often subjected to random disturbances arising from various sources such as motors and external sources. These disturbances may induce randomly distributed forces and random torques on the structure and hence a stable system may produce additional additive angular motion of the rigid body. If these disturbances persist in the absence of appropriate control, then small motion excitation from one part of the system may build up and lead to instability of the entire system. Moreover, the flexible structure in theory is characterised as a distributed-parameter system with infinite number of modes, which makes it difficult to control, while controller design for flexible spacecraft is in general based on an approximated finite-dimensional model by truncating the infinite number of modes to a finite number through neglecting the higher frequency modes. Hence, flexible spacecraft control design needs to take into account disturbance rejection as well as model uncertainty.

Advances in modelling has provided a wide variety of artificial intelligence design techniques in addition to the more traditional approaches, such as recursive least square which have been applied to flexible manoeuvring systems. Nowadays hybrid approaches of such intelligent techniques have evolved into powerful modelling methodologies, solving challenging nonlinear modelling problems.

The adaptive network based fuzzy inference system (ANFIS) concept was first introduced by Prof. J. S. Roger Jang in National Tsing Hua University. The model represents a neural network approach combined with fuzzy inference system based on Takagi-Sugeno inference model [1 – 3].

ANFIS is a hybrid learning algorithm which uses the learning ability of neural networks to adjust the membership function parameters in a fuzzy inference system in order to build the adaptive system. Fuzzy inference can provide rule base generation from human experts' knowledge whereas the neural network approach supports tuning of membership function parameters from input output data pairs [3].

The twin rotor multi-input multi-output system (TRMS) is an ideal laboratory test bed representing a highly nonlinear flexible manoeuvring system, in which the system response involves both rigid body motion and flexible motion dynamics. There have been several studies about the control of flexible manoeuvring systems such as the TRMS. Previous works done include neural networks [4], genetic algorithm [5], analytical and empirical approaches [6], and ANFIS for vertical motion [7].

This paper investigates modelling of the TRMS in both planes, vertical (pitch angle) and horizontal (yaw angle) using ANFIS techniques.

II. TRMS SETUP

The TRMS is a laboratory scale set-up designed for control experiments by Feedback Instruments Ltd. [8]. It is an aero-dynamical system similar to a helicopter as shown in Fig. 1. It consists of a beam pivoted on its base in such a way that it can rotate freely in both its horizontal and vertical planes producing two rotating movements around yaw and pitch axes, respectively. There are two propellers at both ends driven by DC-motors. The articulated joint allows the beam to rotate in such a way that its ends move on spherical surfaces. There is a counter-weight fixed to the beam to determine a stable equilibrium position. The system is balanced in such a way, that when the motors are switched off the main rotor end of the beam is lowered down due to its weight.

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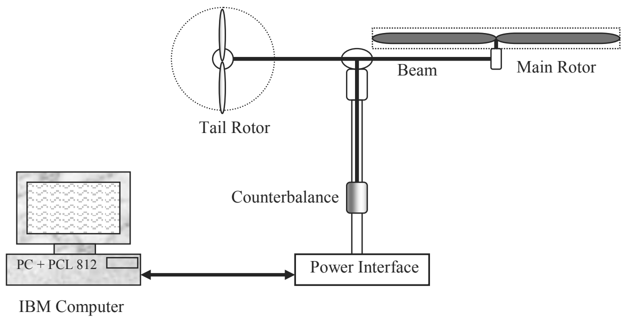

Figure 1. Schematic diagram of the TRMS

In a typical helicopter, the aerodynamic force is controlled by changing the angle of attack of the blades. However, in the TRMS the pitch angle of the blades is fixed and the aerodynamic force is controlled by varying the speed of the motors. Therefore, the control inputs are the supply voltages to the DC-motors.

It is important to note that the geometrical shapes of the propellers are not symmetric. Accordingly, the system behaviour in one direction is different from that in the other direction. Rotation of a propeller produces an angular momentum which, according to the law of conservation of angular momentum, is compensated by the remaining body of the TRMS beam. This results in interaction between the moment of inertia of the motors with propellers. This interaction directly influences the velocities of the beam in both planes. The state of the beam is described by four process variables: horizontal and vertical angles measured by optical encoders fitted at the pivot, and two additional state variables are the angular velocities of the rotors, measured by tacho-generators coupled to the driving DC motors. Angular velocities of the beam are software reconstructed by differentiating and filtering measured position angles of the beam.

The static characteristics of each DC-motor with propeller are non-linear in nature. The relation between the rotor's velocity and the resulting aerodynamic force is also non-linear. For 2-DOF motion, in addition to the above factors, the cross-coupling effect from either channel affects the dynamics of each channel and contributes significantly to the overall non-linearity of the system. The system is interfaced with a personal computer through a data acquisition board, PCL-812PG.

III. ANFIS MODELLING

Fig. 2 shows the basic architecture of ANFIS and the function of each layer is described below:

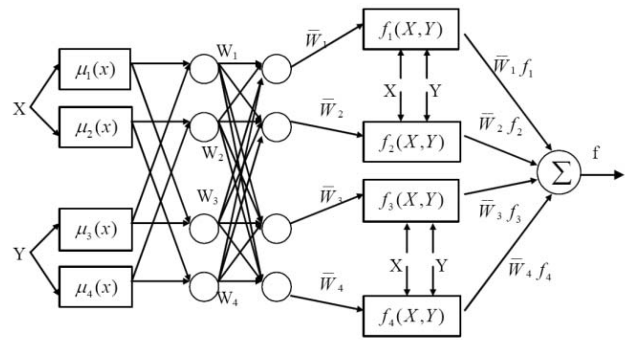

Figure 2. A basic structure of ANFIS

Layer 1 is named as input nodes. In this layer, the membership grades of crisp inputs are generated which fit in to each of suitable fuzzy sets by using the membership functions. The choice of bell-shaped membership function is common as given by:

$$\mu_A(x) = \frac{1}{1+((x-c_i)a_i)^{2b_i}} \tag{1}$$

where, μ_A is the appropriate membership functions for Ai fuzzy set, a_i, b_i, c_i constitute the membership functions parameter set (premise parameters) that changes the shape of membership function from 1 to 0.

Layer 2 is named as rule nodes. The function of this layer is to implement rules operators (AND/OR) in order to obtain the output called as firing strengths corresponding to the result of the antecedent for fuzzy rule. The output of the second layer is the product of the previous signal:

$$O_i^2 = w_i = \mu_A(x)\mu_B(y); \quad i = 1,2 \tag{2}$$

Layer 3 is named as average node and the output of this layer is called normalized firing strength.

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum_i w_i}; \quad i = 1,2 \tag{3}$$

Layer 4 is named as consequent nodes. Every node i in this layer is a square node with a node function:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r); \quad i = 1,2 \tag{4}$$

Where, w_i is the output of layer 3 and p_i, q_i, r constitute the parameter set.

Layer 5 is named as output nodes with single fixed node calculated by:

$$O_i^5 = f(x,y) = \frac{\sum_i w_i f_i}{\sum_i w_i}; \quad i = 1,2 \tag{5}$$

The detailed ANFIS derivation and explanation can be found in [9 – 10].

IV. IMPLEMENTATION AND RESULTS

The method to construct the ANFIS model for the vertical (pitch) and horizontal (yaw) motion is discussed in this section. It is essential to collect real time experimental data for training and testing purposes. The success of a reliable and robust ANFIS network strongly depends on the choice of process variables involved as well as the available data set and the domain used for training purposes [1]. A data set of 1000 points was collected for each manoeuvre; pitch and yaw angle with a random reference input signal. Another data set of 1000 points was obtained for testing purposes.

In order to construct the model for the vertical motion, input signal consisting of three input vectors is used namely reference input signal *(u)* and delayed output samples; *y(t-1)* and *y(t-2)* were used. The membership function for each input was set to be three. Therefore, the ANFIS structure had 27 rules as shown in "Fig. 3". The type of membership function used was the product of two sigmoid functions. In the training process, a hybrid approach was used as optimization method, which comprises a combination of least-squares and back propagation gradient descent method [11]. As a result, the obtained model achieved mean-squared error (MSE) level of 0.0024484 after 100 epochs.

For horizontal motion, the same network structure was deployed except the choice of membership function was Gaussian instead of product of two sigmoid functions. Therefore the ANFIS structure will be exactly the same as for the vertical motion as shown Fig. 3. After training for 100 epochs using the hybrid approach, the model achieved an MSE level of 0.0022861.

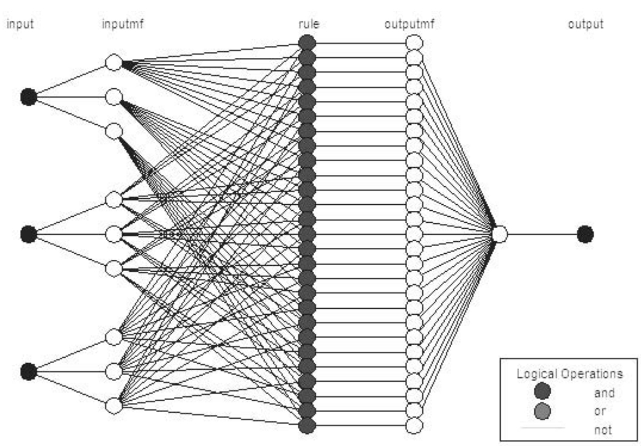

Figure 3. ANFIS structure for modelling the system

Fig. 4 shows that the actual and predicted output for vertical motion, and the corresponding error signal is shown in Fig. 5. It is noted that the ANFIS model predicted the real TRMS in vertical motion well. However, further model validation techniques are still needed in order to assess the accuracy of the model.

Fig. 6 demonstrates the power spectral density of the system response in vertical motion. The characteristics of the main body dynamics indicate that the main resonance mode for the system is 0.39 Hz. The correlation validation results are shown in Figs. 7 – 11. Fig. 7 displays the autocorrelation of the error signal whereas Figs. 8 – 11 show the cross-correlation signals. All the correlation test signals are within the 95% confidence bands indicating that the model behaviour is close to that of the real system.

Fig. 12 shows that the actual and predicted output for horizontal motion and the corresponding error signal is shown in Fig. 13. It is noted that the ANFIS model predicted the real TRMS response well. In order to examine the accuracy of the model, further model validation techniques are implemented.

Fig. 14 demonstrates the power spectral density of the system response in horizontal motion. The characteristics of the main body dynamics indicate the same behaviour like vertical motion where the main resonance mode for this system is 0.39 Hz. The correlation validation results are shown in Figs. 15 – 19. Fig 15 shows the autocorrelation of error signal whereas Figs. 16 – 19 show the cross-correlation signals. All the correlation test signals are within the 95% confidence bands indicating that the model behaviour is identical to the real system behaviour.

V. CONCLUSION

In this investigation, ANFIS technique has been used to build models for vertical and horizontal motion of the TRMS. The obtained results indicate that both models are accurate and the errors are within the acceptable range.

Model validations based on power spectral density and correlation techniques have been conducted. These analyses have shown that the obtained models represented the real TRMS closely.

In conclusion, ANFIS modelling technique is powerful to facilitate modelling of complex systems associated with nonlinearity and uncertainty. As further work, the obtained ANFIS models will be used to develop an intelligent control scheme for the system.

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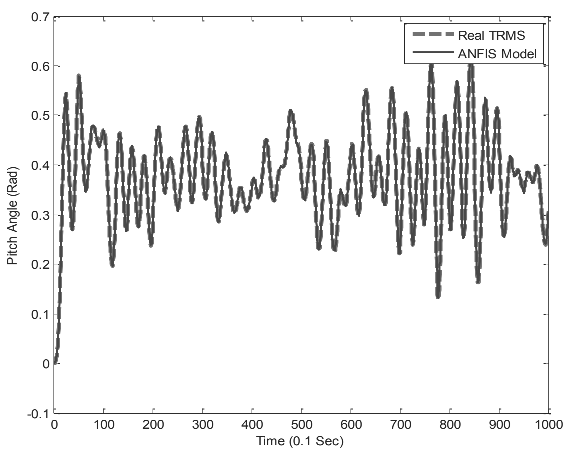

Figure 4. Actual and predicted model of pitch motion

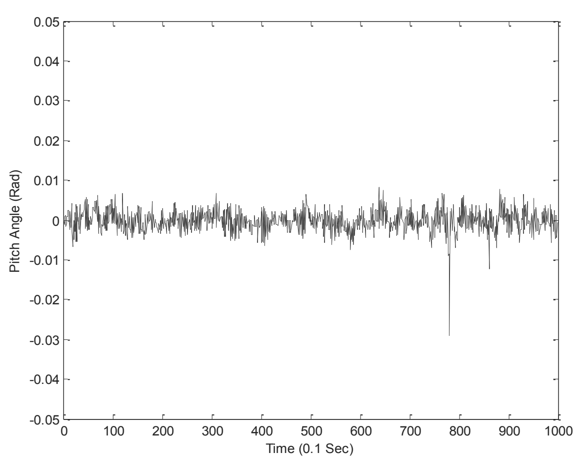

Figure 5. The Error between actual and predicted output

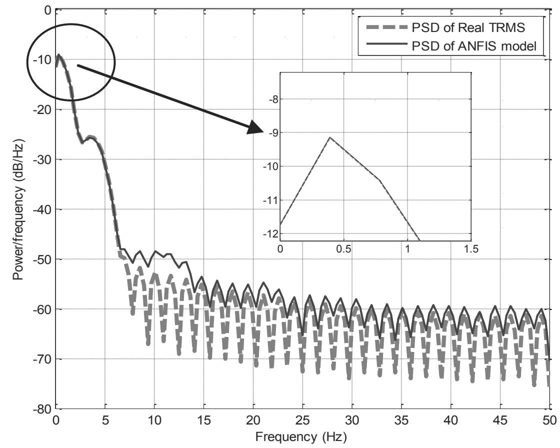

Figure 6. Power spectral density of pitch motion of TRMS

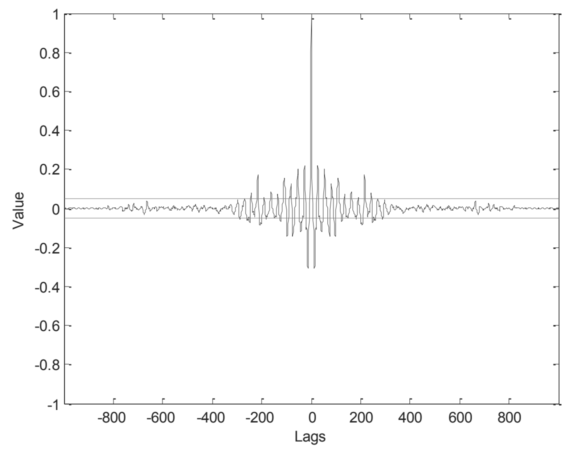

Figure 7. Autocorrelation of residual (pitch model)

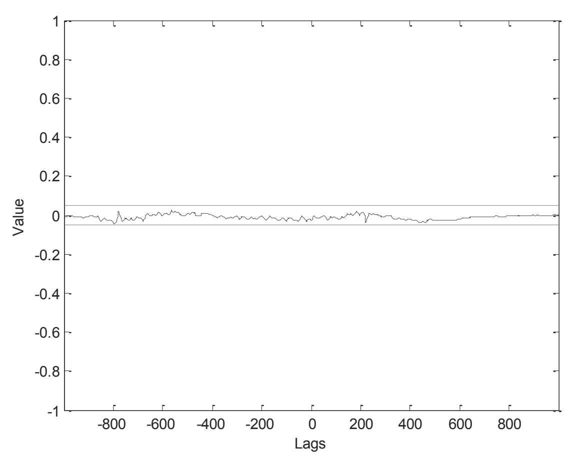

Figure 8. Cross-correlation of input and residual (pitch model)

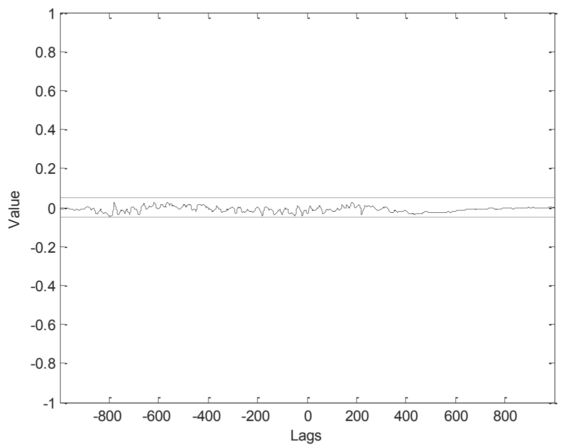

Figure 9. Cross-correlation of input square and residual (pitch model)

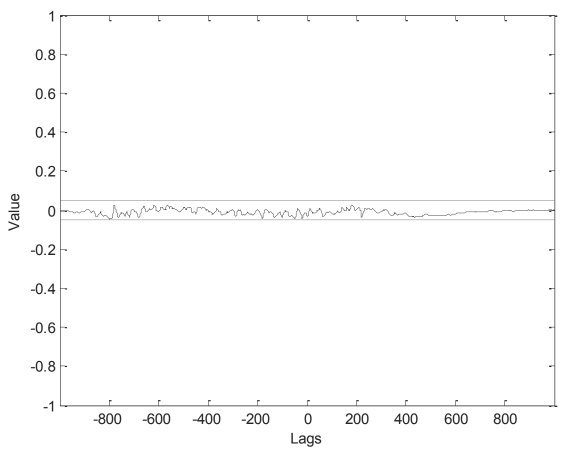

Figure 10. Cross-Correlation of input square and residual square (pitch model)

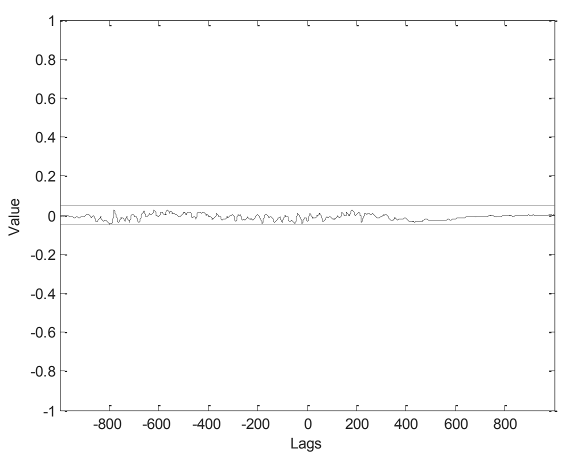

Figure 11. Cross-correlation of input residual and residual (Pitch Model)

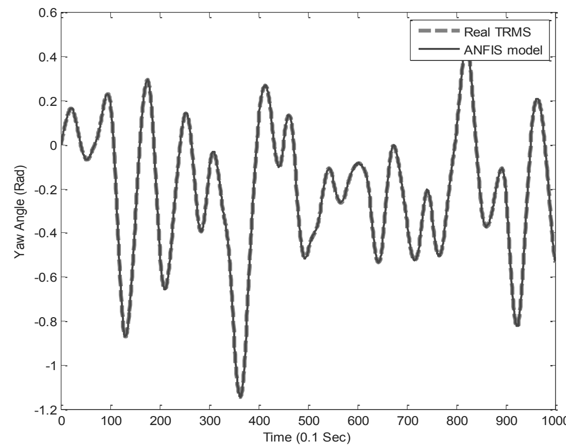

Figure 12. Actual and predicted yaw motion of TRMS

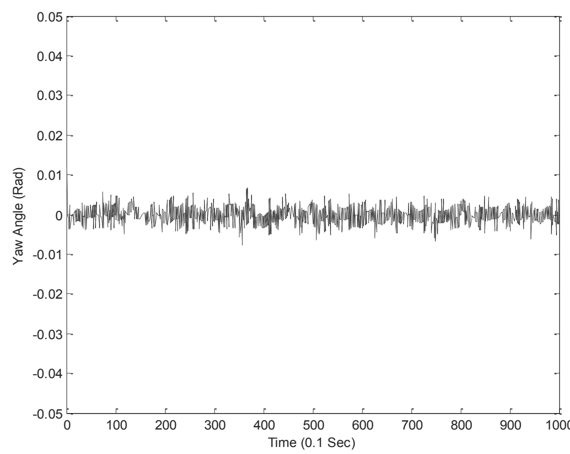

Figure 13. The Error between actual and predicted yaw motion

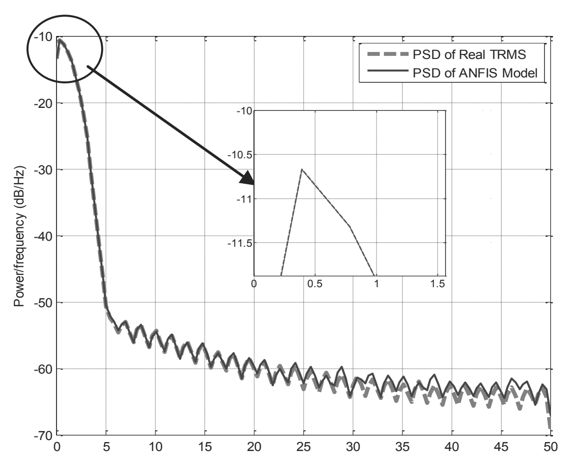

Figure 14. Power spectral density of yaw motion

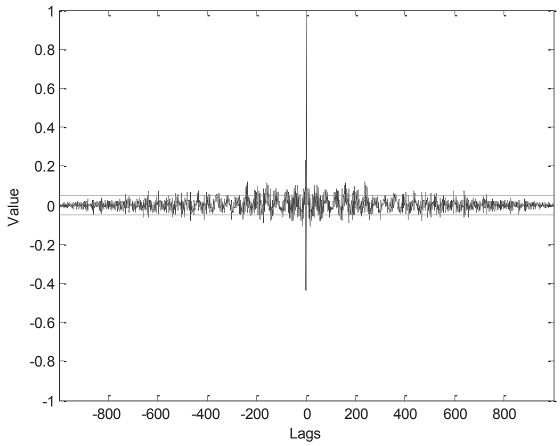

Figure 15. Autocorrelation of residual (yaw model)

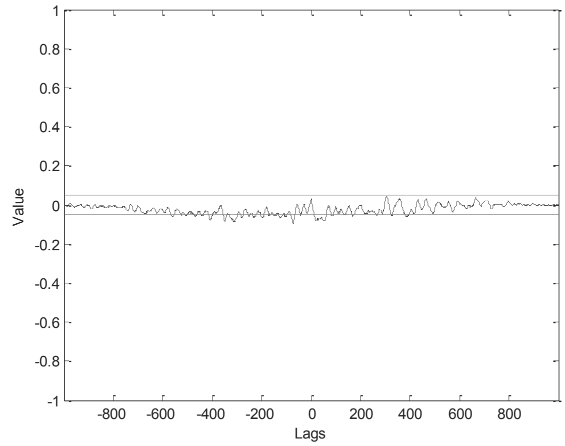

Figure 18. Cross-correlation of input square and residual square (yaw model)

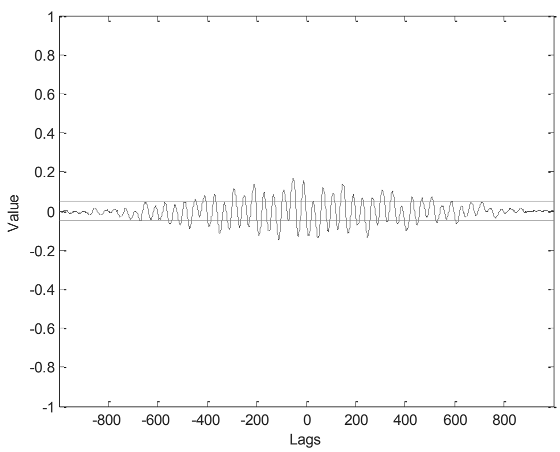

Figure 16. Cross-correlation of input and residual (yaw model)

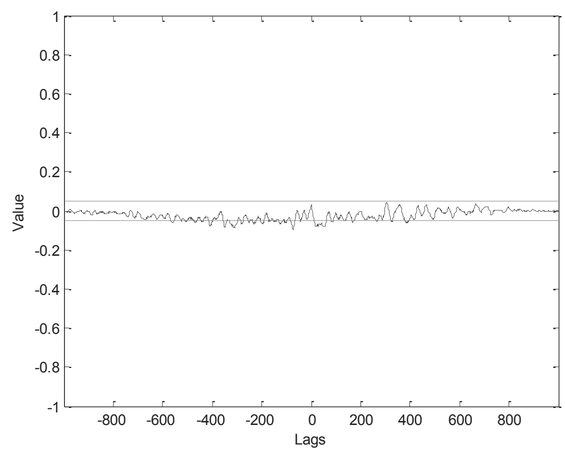

Figure 19. Cross-correlation of input residual and residual (yaw mode)

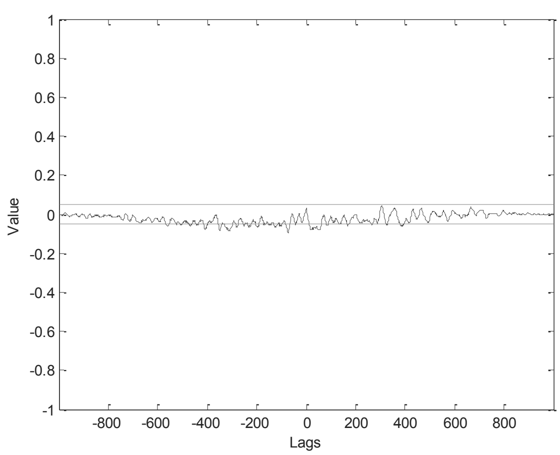

Figure 17. Cross-correlation of input square and residual (yaw model)