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On Comparison of Neural Observers for Twin Rotor MIMO System

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Abstract

This paper presents a comparative study of neural observers for TRMS. These are Chebyshev neural network based observer (CNN) and Multi-layer feed-forward neural network (MLFFNN) observer. TRMS is a highly non-linear system having mutual interference between two rotors, it is trivial to design an effective controller for the TRMS to reach the desirable yaw and pitch angles. All the states are not available for the measurement, so to estimate the inaccessible states of TRMS these non-linear state observers are designed. On Comparing Performance MLFFNN found to be better than CNN observer.

Keywords- Twin rotor multi input multi output system (TRMS), Chebyshev neural network (CNN) and Multi-layer feed-forward neural network (MLFFNN), Degree of freedom (DOF).

Introduction
Many real physical systems are nonlinear in nature. Controlling nonlinear systems is a difficult problem due to their complex nature. This problem becomes more acute when the system's parameters are uncertain. Uncertainty affects decision-making and appears in a number of different forms. It is an inherent part of real world systems and the observers designed for such uncertain systems are required to act in an appropriate manner and eliminate the effect of imprecise information.

Model description
TRMS is a laboratory prototype of a flight control system. It is a multi-input-multi-output (MIMO) nonlinear system, with substantial cross coupling between main rotor and tail rotor with degrees of freedom on the pitch and yaw angle denoted by ψ and ϕ

respectively. The main rotor produces a lifting force allowing the beam to rise vertically (pitch angle), while the tail rotor is used to control the beam to turn left or right (yaw angle). Both motors produce aerodynamic forces through the blades. The mechanical and electrical units provide a complete control system setup.

The TRMS mechanical unit consists of two rotors which are perpendicular to each other and joined by a beam pivoted on its base, so that it can rotate freely in both horizontal and vertical planes. To make the TRMS stabilized a counterbalance arm with a weight at its end is fixed to the beam at the pivot. At both ends of the beam there are rotors driven by two independent similar DC motors and the angular velocities of the rotors is measured by Tacho generators, attached with the DC motors. TRMS can work with both 1-DOF and 2-DOF using nylon screws. The whole unit is attached to the tower allowing for safe helicopter control experiments. Another important unit is the electrical unit (placed under the tower) plays a vital role for TRMS control which allows the measured signals to be transferred to the PC and control signals to be applied to the system via a PCI-1711 I/O card. The working principle of TRMS is similar to a helicopter with two degrees of freedom (2-DOF)

Modelling of trms

The complete dynamics of the TRMS system can be represented in the state- space form as follows:

$$\frac{d}{dt}\psi = \dot{\psi}$$

$$\frac{d}{dt}\dot{\psi} = \frac{a_1}{I_1}\tau_1^{\ 2} + \frac{b_1}{I_1}\tau_1 - \frac{M_g}{I_1}\sin\psi - \frac{B_{1\psi}}{I_1}\dot{\psi} + \frac{0.0326}{2I_1}\sin(2\psi)\dot{\varphi}^2$$

$$-\frac{k_{gy}}{I_1}a_1\cos(\psi)\dot{\varphi}\tau_1^{\ 2} + \frac{k_{gy}}{I_1}b_1\cos(\psi)\dot{\varphi}\tau_1$$

$$\frac{d}{dt}\varphi = \dot{\varphi}$$

$$\frac{d}{dt}\dot{\varphi} = \frac{a_2}{I_2}\tau_2^{\ 2} + \frac{b_2}{I_2}\tau_2 - \frac{B_{1\varphi}}{I_2}\dot{\varphi} - 1.75\frac{k_c a_1}{I_2}\tau_1^{\ 2} - \frac{1.75}{I_2}k_c b_1\tau_1$$

$$\frac{d}{dt}\tau_1 = -\frac{T_{10}}{T_{11}}\tau_1 + \frac{k_1}{T_{11}}u_1$$

$$\frac{d}{dt}\tau_2 = -\frac{T_{20}}{T_{21}}\tau_2 + \frac{k_2}{T_{21}}u_2$$

The output is given by

$$y = [\psi \quad \varphi]^T \tag{1}$$

Where,

Ψ: Pitch (elevation) angle

τ_1 : Momentum of main rotor
ϕ: Yaw (azimuth) angle
τ_2 : Momentum of tail rotor

Chebyshev neural network based observer
We consider the Chebyshev polynomials as basis functions for the neural network. The Chebyshev polynomials can be generated by the following recursive formula

$$T_{i+1}(x) = 2xT_i(x) - T_{i-1}(x),\ T_0(x) = 1 \tag{2}$$

Where $T_i(x)$ is a Chebyshev polynomial i is the order of polynomials chosen and here x is a scalar quantity. The architecture of the CNN consists of two parts; numerical transformation part and learning part. Numerical transformation deals with the input to the hidden layer by approximate transformable method. The transformation is the functional expansion (FE) of the input pattern comprising of a finite set of Chebyshev polynomials. As a result the Chebyshev polynomial basis can be viewed as a new input vector. The network is shown in Fig.1. The output of the single layer neural network is given by

$$f(x,u) = W\phi(x,u) + \varepsilon(x) \tag{3}$$

Where, W is the weights of the neural network and $\varepsilon(x)$ is the CNN functional reconstruction error vector.

An estimate of can be given by,

$$\hat{f}(x,u) = \hat{W}\phi(\hat{x},u) \tag{4}$$

Where, W is the estimate of the ideal weight and

$$\phi(\hat{x},u) = [1 \quad T_i(\hat{x}_1) \quad T_i(\hat{x}_2) \quad \ldots \quad T_i(\hat{x}_6) \quad T_i(u_1) \quad T_i(u_2)]^T \tag{5}$$

Here the order of the function i is taken as 2.
Designing of the observer is given by,

$$\begin{aligned} \dot{\hat{x}}(t) &= A\hat{x} + \hat{W}\phi(\hat{x},u) + K(y - \hat{y}) \\ \hat{y}(t) &= C\hat{x} \end{aligned} \tag{6}$$

Multilayer Feed Forward Neural Network
Here we are taken single input, one hidden and one output layer of feed forward neural network and for learning of neural network back propagation algorithm is used. In Back propagation, for learning feed forward neural Network uses gradient descent technique in weight updating. Weights are updated at each iteration and derivative being re-evaluated for each new set of weights according to the expression

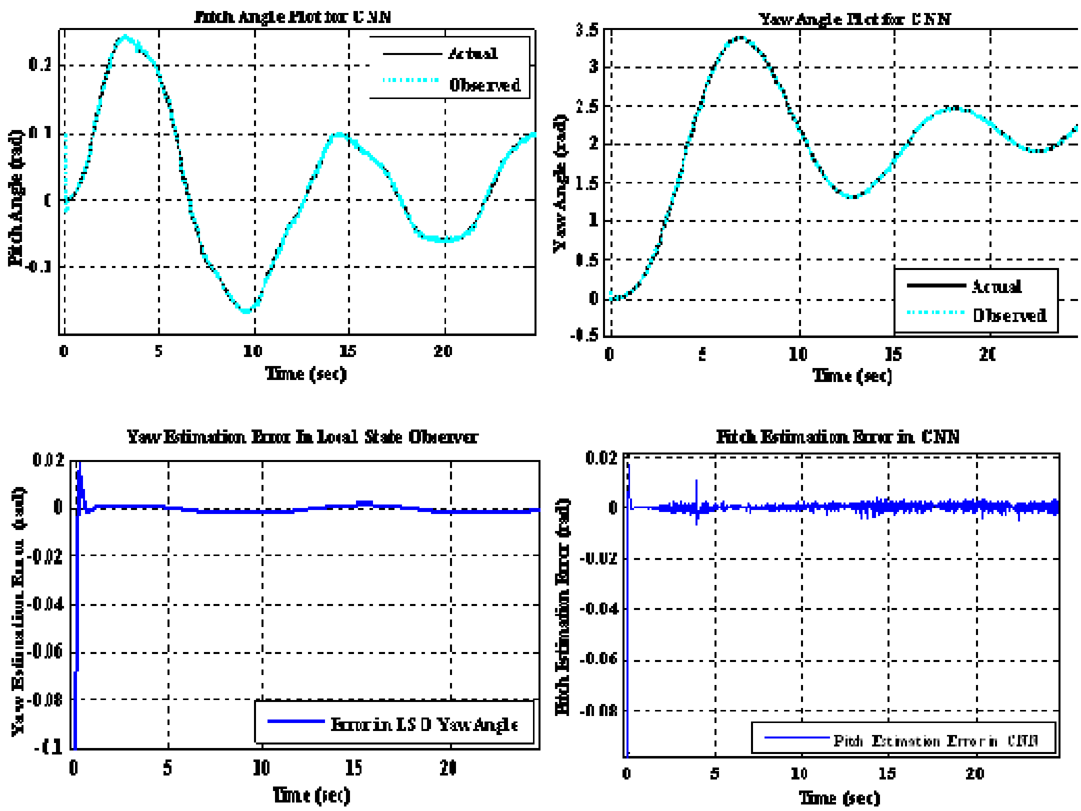
$$\Delta w_{ji}^{(\tau)} = -\alpha \frac{\partial E}{\partial w_{ji}}\bigg|_{w^{(\tau)}} + \eta \Delta w_{ji}^{(\tau-1)} \qquad (7)$$

Where τ denotes number of steps in learning cycle and the parameter α is called learning rate. The second term is used to improve the stability of learning process and is called momentum term, with η being momentum rate

VI. SIMULATION RESULTS

A. CNN Based Observer.

The input signal to the plant is given by u1= u2 = 0.2sin (0.4t) + 0.4sin (0.6t) + 0.05sin (0.8t) and initial conditions of the plant and observer is [0 0 0 0 0 0] and [0.1 0 0.1 0 0 0]. The closed loop poles for CNN is chosen as -5, -10, -20, -30, -40, -50 which lies on the left half of the s-plane. The weights of NN are generated randomly and learning rate $\eta = 0.6$ are and iterations $\rho = 500$. Figure shows the tracking of pitch and yaw angles and also their respective estimation errors.



B. Multi-Layer Feed Forward Neural Network

Figure represents the tracking of pitch and yaw angles and also their respective estimation errors.

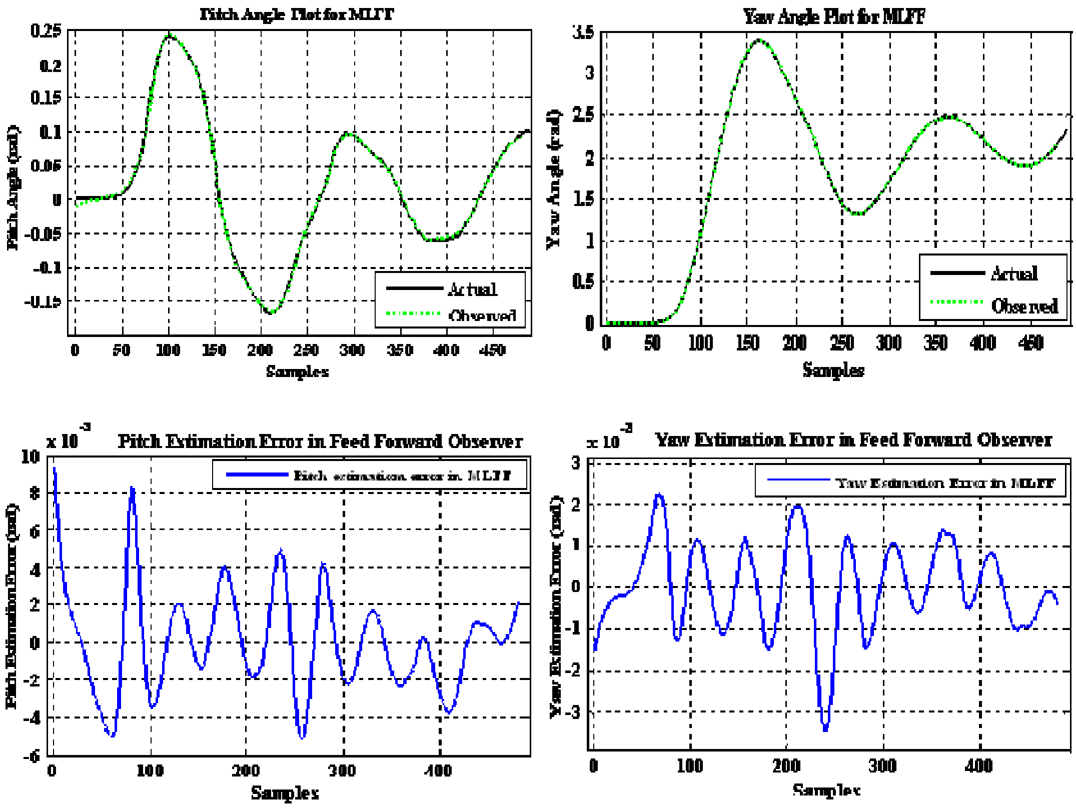


Table I. TRMS SYSTEM PARAMETERS

Parameter	Value	Parameter	Value
I_1=Moment of inertia of vertical rotor	0.068(kg-m^2)	I_2=Moment of inertia of horizontal rotor	0.02(kg-m^2)
a_1=Static characteristic parameter	0.0135	a_2=Static characteristic parameter	0.02
b_1=Static characteristic parameter	0.0924	b_2=Static characteristic parameter	0.09
M_g=Gravity momentum	0.32 (N-m)	$B_{1\Phi}$=Gravity momentum	0.006 (N-m-s/rad)
k_{gy}=Gyroscopic momentum parameter	0.1 (N-m-s/rad)	k_c= Cross reaction momentum gain	-0.2
k_1=Motor 1 gain	0.05(rad/sec)	k_2=Motor 2 gain	1.1
T_{11}=Motor 1 denominator parameter	1	T_{21}=Motor 2 denominator parameter	1
T_P=Motor reaction momentum parameter	2	T_0=Motor reaction momentum parameter	3.5

Table II. COMPARATIVE ERRORS IN NEURAL OBSERVERS DESIGNED FOR TRMS

S.No.	Observers	At time t=10 sec		At time t=20 sec	
		Pitch Angle (10^{-4}) (Degree)	Yaw Angle (10^{-4}) (Degree)	Pitch Angle (10^{-4}) (Degree)	Yaw Angle (10^{-4}) (Degree)
1.	CNN	4.8872	17	4.3441	37
2.	MLFFNN	-4.0828	4.2139	-11	-3.8126

CONCLUSION

In this paper the comparative study of CNN based observer and MLFF neural network are presented. The structures of neural networks are single layer and iterations are kept same for both NN and the performance of both observers was observed. MLFF neural network gives comparatively better results than CNN.

REFERENCES

[1] TRMS 33–949S User Manual. Feedback Instruments Ltd., East Sussex.

[2] B. Pratap, S. Purwar, “Neural Network Observer for Twin Rotor MIMO System: An LMI Based Approach, ” Proceedings of IEEE, International Conference on Modeling, Identification and Control (ICMIC), Okayama, Japan, 2010.

[3] T. T. Lee and J. T. Jeng, “The Chebyshev polynomial based unified model neural networks for function approximations, ” IEEE Transaction on Systems, Man and Cybernetics, Part B, vol. 28 no. 6, pp. 925-935, 1998.

[4] N. H. Jo and J. H Seo, “A State Observer for Nonlinear Systems and its Application to Ball and Beam System, ” IEEE Transactions on Automatic Control, vol. 45, no. 5, pp. 968–973, 2000.

[5] S. Haykins, Neural Networks. Ottawa, Canada: Maxwell Macmillan 2004.

[6] K.S. Narendra and K. Parthasarthy, ’’Identification and control of dynamical system using neural networks, vol.1, pp.4-26, 1990.

[7] F.A. Shaik, S. Purwar, B. Pratap, “Real Time implementation of Chebyshev neural network observer for twin rotor control system, ’’Expert System with applications, 38, 2011, pp.13043-13049.

[8] F. Abdollahi, H.A. Talebi, and R.V. Patel, “A stable neural network observer with application to flexible-joint manipulators, ’’in proc.9¬-th Int. conf. Neural Information Processing, Singapore, 2002, pp.1910-14.