Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnline
CONFERENCE PAPER ARCHIVE

IFAC-PapersOnLine 49-13 (2016) 293–299

Recurrent Interval Type-2 Fuzzy Control of 2-DOF Helicopter With Finite Time Training Algorithm

Erdal Kayacan * **Mojtaba Ahmadieh Khanesar** **

* *School of Mechanical and Aerospace Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798*
E-mail: erdal@ntu.edu.sg
** *Department of Electrical and Control Engineering, Faculty of Electrical and Computer Engineering, Semnan University, Semnan, 35131, Iran*
E-mail: ahmadieh@semnan.ac.ir

Abstract: This study presents the decentralized control of a 2-DOF helicopter by designing a recurrent interval type-2 fuzzy neural network (RIT2FNN). The main aim of the proposed controller is to force the pitch and yaw angles follow a desired trajectory by using a finite time adaptation law. The proposed control signal is composed of two terms: the output of the RIT2FNN and the control signal generated by a conventional proportional-derivative (PD) controller. In the beginning, since the initial conditions of the RIT2FNN are randomly selected and may not be appropriate, the PD controller is responsible for the control of the system. However, the stable adaptation laws, which benefit from sliding mode control theory, train the parameters of the RIT2FNN. Since the adaptation laws are guaranteed to converge in finite time, the parameters of the RIT2FNN converge to their appropriate values. Meanwhile, the PD controller participates less in the control process and the RIT2FNN becomes the dominant controller of the system. The proposed control method is promising when dealing with highly nonlinear real-time systems which have to operate under uncertain working environment.

Keywords: Type-2 fuzzy neural networks, recurrent, sliding mode control, adaptive intelligent control, feedback error learning, 2-DOF helicopter model.

1. INTRODUCTION

Unlike fixed-wing aircrafts, lift and thrust are generated by rotors in helicopters which provides an extra advantage, namely vertical take-off and landing capability. On the other hand, helicopters have significant drawbacks, such as having highly nonlinear dynamics and intercouplings. Therefore, they are used as a benchmark set up to test various control algorithms (Khanesar and Kayacan, 2015; Hervas et al., 2016; Maslim et al., 2015). Not only do they have more complex dynamics but also their operating conditions can often change. Helicopters have to deal with inherent and external uncertainties, e.g. they have to operate under windy environments. Requirements for flight control systems of helicopters include tight performance specifications, ability to account for the model changes, adaptation due to the changes in the operating conditions.

In order to deal with changing operating conditions, model-free or adaptive control methods can be preferred. However, the conventional adaptive control systems may not be capable of controlling these systems with large uncertainties or highly changing parameters (Chen et al., 2015). On the other hand, model free intelligent control algorithms are simpler, and they need less knowledge about the dynamic of the system to be controlled (Kayacan et al., 2015b; Khanesar et al., 2015).

Among model-free approaches, artificial neural networks and fuzzy logic systems are the most popular methods. While the former is well known for its learning capability from input-output data, the latter is capable of using expert knowledge (Kayacan et al., 2015a). The working principle of a fuzzy logic controller is much closer to human way of thinking. In this paper, an adaptive neuro-fuzzy structure, which is the fusion of the two aforementioned model-free methods, is preferred.

In this study, the proposed control action is composed of two terms: the term generated by a recurrent interval type-2 fuzzy neural network (RIT2FNN) and the control signal generated by a proportional derivative (PD) controller. The main reason for using a conventional PD controller is that in the first few seconds of the control process, the parameters of the intelligent controller may not be appropriate for controlling the system since its parameters are often randomly selected. However, the stable adaptation laws, which are based on sliding mode control (SMC) theory in this paper, train the parameters of the intelligent controller. Fortunately, after a finite time, the parameters of the RIT2FNN are trained enough to increase their responsibility to control the system. Eventually, the flexible and adaptive structure of the proposed method helps to increase the control performance of the overall system.

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.07.977

2. SYSTEM DESCRIPTION

The 2-DOF helicopter model is illustrated in Fig. 1. There are two propellers which are perpendicular to each other. Whereas the front propeller is responsible for the control of pitch angle (elevation), the back or tail propeller controls the yaw angle, which are the two system outputs. There are no constraints on the yaw angle of the system (Inc., 2010). In other words, the system can have a full rotation about its yaw axis. The control objective for the system is to force the pitch and yaw angles track any arbitrary time-based desired trajectories. Whereas the required parameters and their numerical values are given in Table 1, the nonlinear dynamic equations of motion are given as follows (Inc., 2010):

$$
\begin{aligned}
(J_p + ml^2)\ddot{\theta} &= K_{pp}V_{m,p} + K_{py}V_{m,y} - mglcos\theta \\
&\quad - B_p\dot{\theta} - ml^2 sin\theta cos\theta\dot{\psi}^2 \\
(J_y + ml^2cos^2\theta)\ddot{\psi} &= K_{yp}V_{m,p} + K_{yy}V_{m,y} - B_y\dot{\psi} \\
&\quad + 2ml^2 sin\theta cos\theta\dot{\psi}\dot{\theta}
\end{aligned} \tag{1}
$$

Table 1. Description of the parameters

	Description	Values
J_p	Total moment of inertia about pitch axis	$0.0384kgm^2$
J_y	Total moment of inertia about yaw axis	$0.0431kgm^2$
l	Center of mass length along helicopter body from pitch axis	$0.1855m$
K_{pp}	Thrust torque constant acting on pitch axis from pitch propeller	$0.2041Nm/V$
K_{py}	Thrust torque constant acting on pitch axis from yaw propeller	$0.0068Nm/V$
K_{yp}	Thrust torque constant acting on yaw axis from pitch propeller	$0.0219Nm/V$
K_{yy}	Thrust torque constant acting on yaw axis from yaw propeller	$0.072Nm/V$
g	Gravitational constant	$9.81m/s^2$
B_p	Viscous damping about pitch axis	$0.8N/V$
B_y	Viscous damping about yaw axis	$0.318N/V$
m	Total moving mass of the helicopter	$1.3872kg$
$V_{m,p}$	Voltage applied to the pitch motor	$\pm 24V$
$V_{m,y}$	Voltage applied to the yaw motor	$\pm 15V$

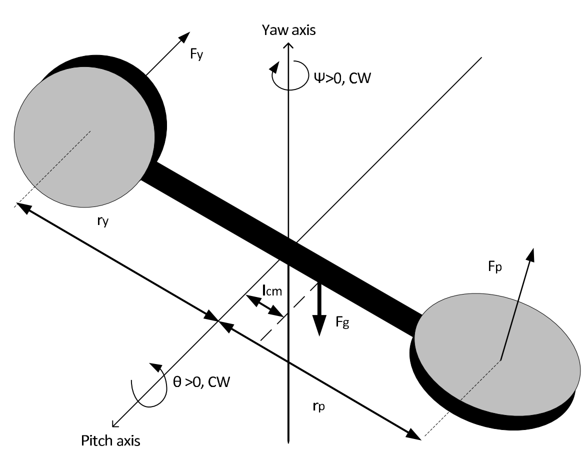

Fig. 1. Free body diagram of 2-DOF helicopter

3. RECURRENT INTERVAL TYPE-2 FUZZY NEURAL NETWORK

The proposed SMC theory-based training method for the RIT2FNN is presented. It is assumed that the PD controller guarantees the stability of the closed loop system. Furthermore, the equation of the classical controller serves as a sliding manifold. The PD control law is as follows:

$$u_c = k_P e + k_D\dot{e}, \; e = T(t) - y(t) \tag{2}$$

where $T(t)$ is the desired trajectory of the system to be followed and $y(t)$ is the output of the system. It is to be noted that this formulation is for one output, whereas there are two outputs in our system. In other words, there are two identical PD controllers and two RIT2FNNs in the system. The parameters k_P and k_D are the proportional and derivative weights of the classical controller, respectively. In the design of the conventional controller, the optimal choice of the gains of the system is difficult. One of the most applicable methods to choose these parameters is the trial-and-error method which is time consuming. However, in the proposed approach the responsibility of the PD controller is only to keep the system stable for a while. The intelligent controller can add more degrees of freedom to the system to enhance the performance of the system. The stability analysis of the adaptation laws of the RIT2FNN are guaranteed using Lyapunov stability theory.

The RIT2FNN employ recurrent type-2 membership functions (MFs). From different types of type-2 MFs, the type-2 MFs with uncertain σ values are selected for the premise part of the proposed system. The structure of this controller is represented in Fig. 2. There are different recurrent structures for type-2 fuzzy systems. We prefer to use the structure which is introduced in (Lee and Chang, 2011; Chang and Lee, 2011).

A sample *if-then* rule R_{ij} of the fuzzy system with two input variables is defined as follows:

$$R_{ij}\text{: } \textit{If } e \text{ is } \widetilde{A}_{1i,k} \text{ and } \dot{e} \text{ is } \widetilde{A}_{2j}, \textit{ then } u_f = f_{ij}$$

where f_{ij} are adaptive crisp values. Furthermore, The mathematical expression for the recurrent type-2 MF studied in this paper is as follows:

$$\tilde{\mu}(x) = \exp\left[-\frac{(x+\xi-c)^2}{\sigma^2}\right] \tag{3}$$

where c is the *center* of the recurrent type-2 MF, σ is the *standard deviation* of the MFs which is considered to be an interval and x is the input. In addition, ξ is the recurrent term which depends on the previous value of the type-2 MF and will be discussed later.

The upper and lower MFs are indicated as: $\overline{\mu}(x)$ and $\underline{\mu}(x)$, respectively. The firing strength of the rule R_{ij} is obtained as follows:

$$\underline{W}_{ij} = \underline{\mu}_{1i}(e)\underline{\mu}_{2j}(\dot{e}) \tag{4}$$

$$\overline{W}_{ij} = \overline{\mu}_{1i}(e)\overline{\mu}_{2j}(\dot{e}) \tag{5}$$

The Gaussian MFs $\underline{\mu}_{1i}(e)$, $\overline{\mu}_{1i}(e)$, $\underline{\mu}_{2j}(\dot{e})$, and $\overline{\mu}_{2j}(\dot{e})$ of the inputs e and $\dot{e}$ are as follows:

$$\underline{\mu}_{1i}(e) = \exp\left[-(\frac{e+\xi_{1i}-c_{1i}}{\underline{\sigma}_{1i}})^2\right] \tag{6}$$