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Autonomous Flight Control Based on Neural Networks and Fuzzy Decision

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Abstract

Autonomous flight has been highly valued by academia and industrial circles. On one hand, it could replace the pilot, cutting down the pilot's training & use costs and solving the problem of pilot's shortage. On the other hand, it could cope with severe weather conditions and emergencies better than the pilot's flight, improving flight safety. The classic control methods used for autonomous flight are mostly about rule-based methods. However their application scenarios are very limited, because the establishment of rules is very difficult. While machine learning based methods are mainly about the low-level behavior learning methods, and the high-level intention learning methods are unusual. This paper presents a new autonomous flight control method in which both the low-level learning and the high-level learning are taken into consideration coordinately. According to the flight stages of take-off, cruise and landing, three clusters of neural networks are built respectively to bridge the gap between flight states and relative actions. At the same time, the idea of fuzzy decision is introduced to implement the top intervention to make a dynamic route adjustment when the route deviates from the predefined target to a certain probability. In the X-Plane flight simulation experiment environment, as the test carrier, the aircraft of Cessna successfully completed the optimal route autonomous flight under different wind-forces, which proved the correctness of the presented method.

Keywords: autonomous flight control, neural networks, fuzzy decision

1. Introduction

Autonomous flight has been highly valued by academia and industrial circles. On one hand, it could replace the pilot, cutting down the pilot's training & use costs and solving the problem of pilot's shortage. On the other hand, it could cope with severe weather conditions and emergencies better than the pilot's flight, improving flight safety.

There are some related programs. The program of Aircrew Labor In-cockpit Automation System (ALIAS) supported by DARPA [1] intends to develop a portable, extensible & tailorable, drop-in & removable kit including hardware and software that enables management of all flight activities. On the premise of minimum modification, an automated assistant working 24 hours a day and 7 days a week will be installed on the existent aircraft to implement the planned activities for the whole flight from take-off to landing even in the face of contingency events such as aircraft system failures. The ALIAS program can be divided to three phases. The objective of Phase I is to demonstrate the performance of the system in a ground-based simulator. The objective of Phase II is to enhance and mature the Phase I system to support the initial flight test on a contractor-sourced aircraft and to demonstrate rapid system portability on the ground, including demonstration of the knowledge acquisition approach. The objective of Phase III is to continue the evolution of the system by porting the system into the specified Phase III flight test aircraft and validating the mission and autonomy interface. Final demonstration will include a flight test activity that exercises the system in command operation for a minimum of 12 hours of flight, including a complete logistics or ISR flight profile from take-off to landing, through contingency events. At now, the previous two phases have been completed and the program goes into Phase III, choosing the performers and evaluating the research schemes.

The program of Common Aircraft Retrofit for Novel Autonomous Control (CARNAC) supported by AFRL [2] has the similar goal. With no access to any aircraft interface, a robot installed on the pilot's chair will execute the flight control by reading the information of all instruments in cockpit including the data displayed on the glass display. CARNAC envisions a robot with the basic software of flight control algorithms that enables to learn the concrete control method to the specified aircraft rapidly. It is expected that the prototype will be introduced in recent years and the autonomous flight test will be performed in a ground-based simulator.

The same also the key point to the success of the above programs is they use AI to help to finish the autonomous flight control. In addition to complete the routine activities, it is able to deal with the uncertain events as well.

Nowadays, the classic flight control methods [3] like the methods of Proportional Integral Derivative control (PID control) and Finite-State Automation control are mostly about rule-based methods. However their application scenarios are very limited, because the establishment of rules is very difficult. Manually designing and developing all the necessary rules covering all possible eventualities to handle the complete spectrum of flight scenarios and uncertainties ranging from normal to emergency situations might be unpractical. While the machine learning based methods developing in recent years are mainly about the low-level behavior learning methods, and the high-level intention learning methods are unusual. Furthermore, they are independent which may not give full play to the two learning methods. [4] & [5] bridge the gap between the low-level learning and the high-level learning. They take them into consideration by neural networks. As is known, if the neural networks play a good role, they must rely on big data. Since the uncertain contingency events during the practical flight are usually small data, it is debatable whether the neural networks are available under this circumstance.

In order to ensure the effective control for the whole flight, this paper presents a new autonomous flight control method in which three clusters of neural networks are built respectively according to the different flight stages to execute the bottom basic control and the idea of fuzzy decision is introduced to implement the top intervening control to the uncertain contingency events.

2. Technical Model

2.1 General Framework

The general framework is shown in Figure 1. The neural networks based flight control module which is at the bottom of the model is used for the basic routine control mapping the flight attitudes with their relative actions. The fuzzy decision based flight control module which is at the top of the model is composed of different sub modules, such as the modules of flight data acquisition, flight status evaluation, route fuzzy calculation, route deviation judgment and status parameters adjustment. They are used for the intervention when the route deviates from the predefined target to a certain probability, making a dynamic route adjustment.

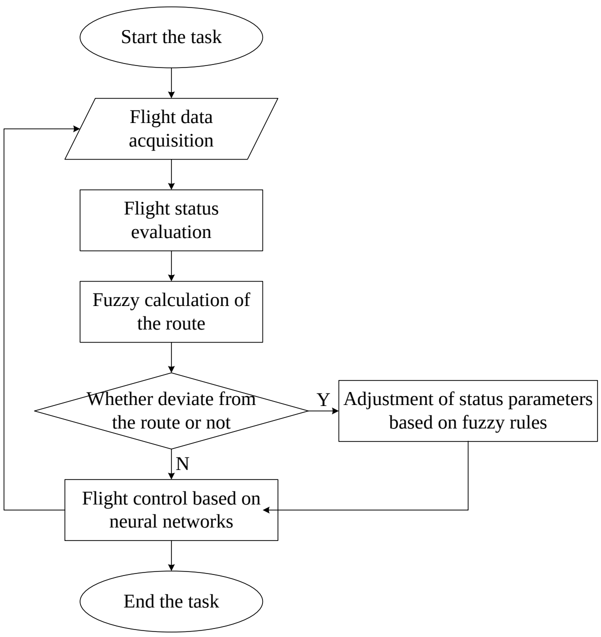


Figure 1 - General framework

2.2 Neural Networks Based Flight Control

According to the flight stages of take-off, cruise and landing, three clusters of forward neural networks are built respectively. As the core of the bottom control, these neural networks execute the specific flight actions in real time with the changing flight attitudes.

The topologies of the neural networks are shown in Figure 2. Based on a rule-of-thumb [6], all the neural networks have only one hidden layer, because problems requiring more than one hidden layer are rarely encountered in the field of control. Furthermore, to avoid under-fitting caused by too few neurons in the hidden layer or over-fitting caused by too many neurons, the number of hidden neurons is set to twice the number of the input neurons.

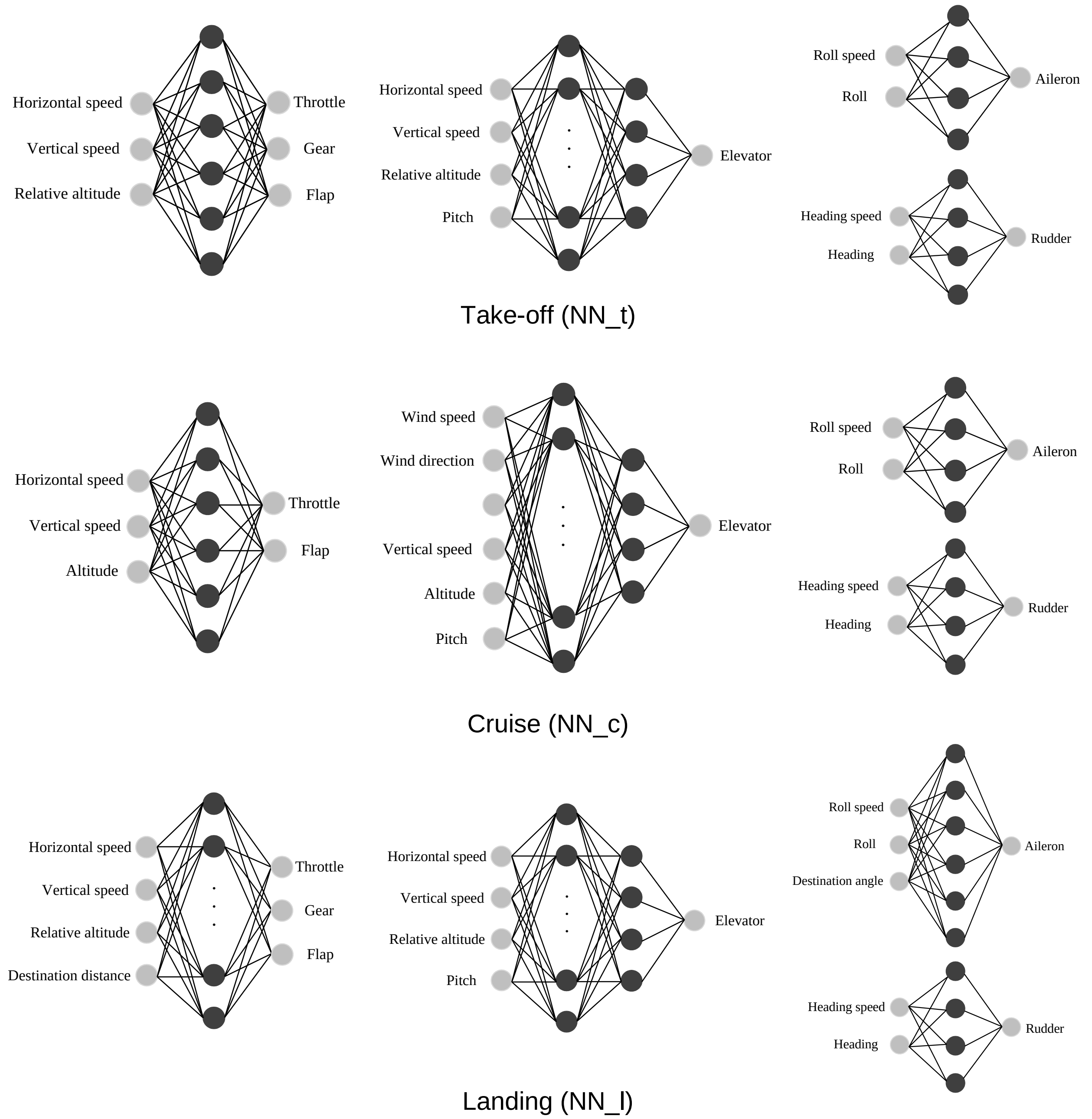


Figure 2 - Topologies of the neural networks

The activation functions have two types: Sigmoid (Equation (1)) and Hyperbolic Tangent (Tanh) (Equation (2)). The Sigmoid function is used by the neural networks in which all input and output values are positive, while the Tanh function is used by the ones in which the datasets contain a few of negative values.

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$f(x) = \frac{e^{2x}-1}{e^{2x}+1} \tag{2}$$

The coefficients of weights and biases are updated by the method of backpropagation. It is to be noticed that different error calculators should be applied based on the different activation functions.

$$\delta_n = (t_n - a_n) a_n (1-a_n) \tag{3}$$

$$\delta_n = (t_n - a_n)(1-a_n)(1+a_n) \tag{4}$$

2.3 Fuzzy Decision Based Flight Control

In light of the status evaluation results at three degrees of freedom relative to the route point like the distance, horizontal direction and the vertical direction, a fuzzy controller is designed to adjust the status parameters based on fuzzy rules.

The inputs of the fuzzy controller are defined as the distance *d* between the aircraft and the route point, the angle *rh* between the aircraft and the route point in the horizontal direction, and the angle *rv* between the aircraft and the route point in the vertical direction. The output of the fuzzy controller is defined as the variation in adjustment of status parameters.

Using continuous domain, the input variable *d* is partitioned as {N, F}, while N represents the air-craft is near to the route point and F represents the aircraft is far from the route point. *rh* is partitioned as {NR, PL, ZM}, while NR represents the aircraft is on the right side of the route point, PL represents the aircraft is on the left side of the route point and ZM represents the aircraft and the route point have the same heading direction. *rv* is partitioned as {NU, PD, ZH}, while NU represents the aircraft is above the route point, PD represents the aircraft is under the route point and ZH represents the aircraft and the route point are at the same height.

Also using the continuous domain, the output variable is partitioned as {FRAR, SRAR, RAM, SRAL, FRAL, FEU, SEU, EM, SED, FED}, while FRAR represents the aircraft needs to roll right with a high speed, SRAR represents the aircraft needs to roll right with a low speed, RAM represents the aircraft needs to maintain the current heading direction, SRAL represents the aircraft needs to roll left with a low speed, FRAL represents the aircraft needs to roll left with a high speed, FEU represents the aircraft needs to ascend with a high speed, SEU represents the aircraft needs to ascend with a low speed, EM represents the aircraft needs to maintain the current height, SED represents the aircraft needs to descend with a low speed, FED represents the aircraft needs to descend with a high speed.

The membership function adopts the form of Gauss, as shown in Figure 3. And the fuzzy rules are built in Table 1.

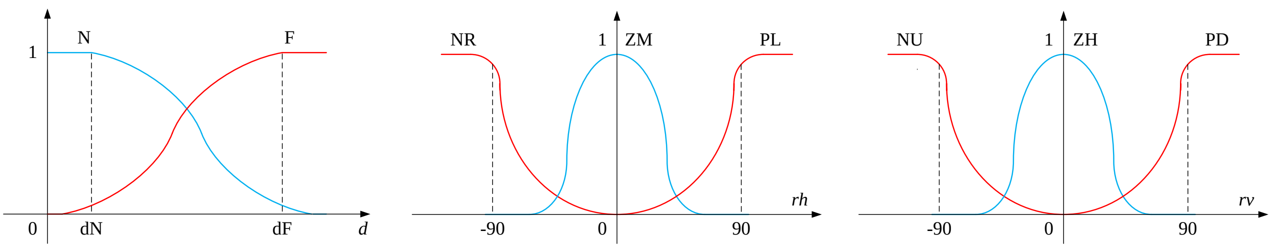


Figure 3 - Membership functions of input variables based on the form of Gauss

Table 1 - Fuzzy rules

Domain partition of *rv*	Domain partition of *rh*	Domain partition of *d*			
		N		F	
NU	NR	FED	FRAL	SED	SRAL
	ZM	FED	RAM	SED	RAM
	PL	FED	FRAR	SED	SRAR
ZH	NR	EM	FRAL	EM	SRAL
	ZM	EM	RAM	EM	RAM
	PL	EM	FRAR	EM	SRAR
PD	NR	FEU	FRAL	SEU	SRAL
	ZM	FEU	RAM	SEU	RAM
	PL	FEU	FRAR	SEU	SRAR

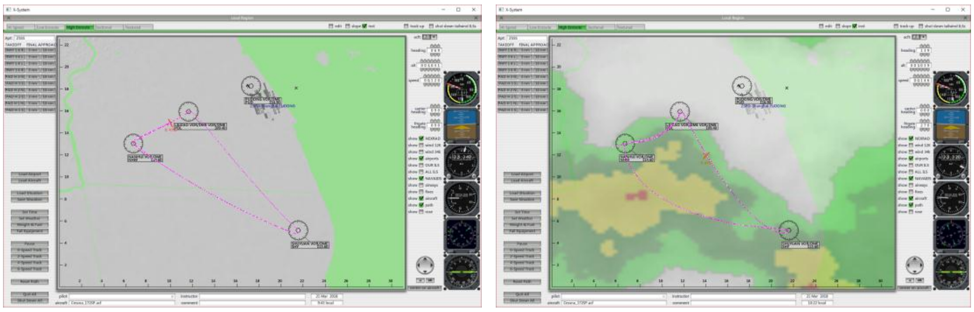
3. Simulation Experiments

Since X-Plane is an advanced flight simulator that has been used in many research papers such as [7] [8] [9] and by multiple organizations and industries such as FAA, NASA, Boeing and Cessna, it is chosen as the simulator to build the simulation experiment environment. In order to demonstrate the advancement of the designed flight control model, the aircraft of Cessna is chosen as the test carrier, because Cessna belongs to a kind of small aircrafts whose flight is more vulnerable to the weather conditions.

There are two weather conditions: with no wind that the wind-force is level of 0-1 and with wind that the maximum wind-force is level of 7. As shown in Figure 4 and Figure 5, the Cessna successfully completes the optimal route autonomous flight under different wind-forces, which proves the correctness of the designed model.

Take-off Cruise Landing

Figure 4 - Some selected pictures of X-Plane simulation experiments



Wind-force: level of 0-1 Maximum Wind-force: level of 7

Figure 5 - Comparison of routes under different wind-forces

4. Conclusion and Future Works

This paper presents a new autonomous flight control method based on the integration of neural net-works and fuzzy decision to take the low-level behavior learning and the high-level intention learning into consideration coordinately. And the simulation experiments demonstrated the correctness of the presented method.

To enhance its practicability, e.g. to use it for the personal autonomous aircraft, some technical problems must be solved further.

- ✧ Knowledge representation and acquisition of the pilot’s experience.
- ✧ Autonomous flight task planning and re-planning based on historical and current flight data.
- ✧ Autonomous navigation based on low cost avionics system.
- ✧ Non-invasive interaction for the aircraft and the ground-based monitor.

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6. Copyright Statement

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