Applying BELBIC (Brain Emotional Learning Based Intelligent Controller) to an Autolanding System

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Abstract- During landing, aircrafts have to face low-altitude wind shear that can be fatal. Most commercial aircrafts currently have optimal automatic landing systems, but they are activated only if well-specified wind speed limitations are met. The reason is that these autolanding systems are not designed to work in the presence of strong wind gusts. In this paper, we apply a modified version of brain emotional learning based intelligent controller (BELBIC) to the autolanding system whose multivariable and non-minimum phase nature make the task difficult. By comparing the results with the results derived from using a high-gain controller, we show that our proposed solution can achieve robust and satisfactory performance.

Key-word:-BELBIC, Autolanding System, Vertical Velocity, Altitude.

1 Introduction

Low-altitude wind shear has been recognized as a serious threat to the safety of aircraft in takeoff and landing [1]. The problem of guiding an aircraft encountering wind shear has received considerable attention. The research effort has been pursued in several directions. These include optimization techniques to determine optimal or near-optimal trajectories and guidance strategies in the presence of wind shear [2]-[4]. However, these techniques assume either global [2], [4], or local [3] prior knowledge of wind profiles, and therefore ensure survival capability only in the prescribed wind shear structure. In addition, they are not easily implementable in practical flight automatic controller because of the amount of computation involved.

Another direction of research has been concerned with the design of automatic landing systems [5]-[7]. In [5], an automatic landing controller design is based on a single-input-single-output model using U-parameter synthesis, where the only controlled variable is the flight path angle. However, other variables are also important to be controlled during landing through a wind shear, for instance, the rate of decent. Using $H\infty$ synthesis theory, [6] presents the design of a flare mode for automatic landing, but does not treat the robustness of the controller in the presence of wind shear. An attempt to design a neural network autolanding system is presented in [7]. Using a backpropagation algorithm, the neural network is trained with set of input/output of a linear-conventional controller and with pilot responses under a variety of wind conditions. Other investigations have been concerned with modeling, prediction, and detection techniques of wind shear and microburst [8], [9].

The object of this paper is to suggest another control approach, which is based on brain emotional learning intelligent controller (BELBIC), in order to achieve an appropriate response. As the essential elements used in previous utilization of BELBIC [12] proved inadequate, we used another model, which includes delay elements to handle the non-minimum-phase behavior [13]. In the proceeding section, we discuss the autolanding system. Then in section 3 we explain our proposed controller, and finally the simulation results and the conclusion are presented in section 4 and 5.

2 System Description

In the literature, the development of aircraft equations of motion has received a great deal of attention [10], [11]. This development proceeds from a consideration of the aerodynamic forces and moments and from the application of the fundamental laws of mechanics. In general, these equations of motion are nonlinear and do not have a tractable form. In [10], the total motion is considered as composed of two parts: a mean motion that is representative of the operating point, and a dynamic motion that accounts for small increments (or perturbations) about the mean motion. Consequently, the equations of motion characterize the incremental aircraft dynamics. For the design of automatic flight control systems, our system found in [12] is a valid approximation of the original nonlinear model [10].
In this paper only longitudinal motion (motion in a vertical plane) is considered during the landing. Lateral motion is required primarily to point the aircraft down the runway and it is assumed that most of it is accomplished prior to the landing.
The longitudinal equations of motion are:

$$\begin{aligned}
\dot{u} &= X_u(u-u_g) + X_w(w-w_g) + X_q q - g\frac{\pi}{180}\cos\gamma_0\theta \\
&\quad + X_E\delta_E + X_T\delta_T \\
\dot{w} &= Z_u(u-u_g) + Z_w(w-w_g) + (Z_q - \frac{\pi}{180}U_0)q \\
&\quad + g\frac{\pi}{180}\sin\gamma_0\theta + Z_E\delta_E + Z_T\delta_T \\
\dot{q} &= M_u(u-u_g) + M_u(w-w_g) + M_q q + M_E\delta_E \\
&\quad + M_T\delta_T \\
\dot{\theta} &= q \\
\dot{d} &= -w + \frac{\pi}{180}U_0\theta
\end{aligned} \tag{1}$$

where
u, w: incremental longitudinal and vertical velocity components (ft/sec), respectively,
u_g, w_g : horizontal and vertical wind gusts velocity components (ft/sec), respectively,
q, θ, d: incremental pitch rate (deg/sec), pitch angle (deg), altitude (ft),
δ_E, δ_T : elevator deflection (deg), engine power control deflection (throttle setting),
$X_u, X_w, X_q, X_E, X_T, Z_u, Z_w, Z_q, Z_E, Z_T, M_u, M_q, M_E, M_T$:
stability derivatives of aircraft,
U_0, γ_0, g : nominal speed (235 ft/sec), flight path angle (-3 deg), gravity (32.2 f/s^2).
The values of the stability derivatives, given in Appendix, are the same used in [7]. The differential equations provide the time behavior of longitudinal and vertical speeds u and w, pitch rate q, pitch angle θ, and altitude d in response to elevator and throttle setting commands δ_E and δ_T, and horizontal and vertical wind gust speeds u_g and w_g.

The plant inputs are:

$$u = \begin{bmatrix} \delta_E \\ \delta_T \end{bmatrix} \tag{2}$$

δ_E : Elevator deflection, δ_T : Throttle setting

The altitude rate $\dot{h}$ is very important in the flight control of an aircraft during landing. It is obtained without actually deriving a rate from the altitude d. this signal is derived from a barometric rate of climb and accelerometer sensors [11].
$\dot{h}$ is given by:

$$\dot{h} = -U_0\sin\delta_0 - w\cos\gamma_0 + u\sin\gamma_0 + \frac{\pi}{180}U_0\cos\gamma_0\theta \tag{3}$$

however,

$$\dot{d} = -w + \frac{\pi}{180}U_0\theta \tag{4}$$

Note that for $\delta_0 = 0$, $\dot{d} = \dot{h}$.

The measured variables adopted here are the altitude d and the rate of climb $\dot{h}$.

The desired outputs are $y = [d, \dot{h}]^T$.

The closed loop longitudinal landing system is shown in Fig.1. The guidance is provided by an airportbased system, called the Instrument Landing System (ILS), which provides the altitude (the beam) and the vertical speed commands. The magnitude of the altitude rate of the aircraft is very important primarily at touchdown. To prevent the aircraft from floating down the runway and hence overshooting it, the altitude rate must be different from zero at the touchdown. The altitude rate, on the other hand, must not be very large because, otherwise, it might overstress the landing gear. A permissible value is between –3 and –1 ft/sec.

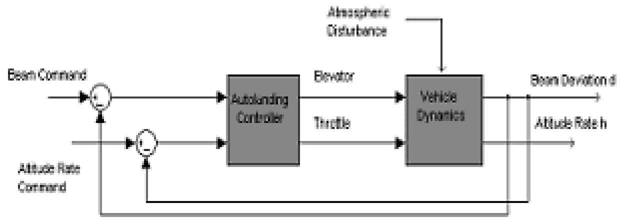

Fig.1 Control system for vertical plane landing

3 BELBIC Controller

BELBIC is the abbreviation for brain emotional learning based intelligent controller, whose description is reported in [13]. Functional modeling of emotions in control engineering was first represented in [17], [18], [19]. Motivated by this approach in [13] a structural model based on the limbic system of mammalian brain [16], for decision making and control engineering application has been developed. The schematic structure of BELBIC is illustrated in fig.2. The main parts, responsible for performing the learning algorithm, are orbitofrontal cortex and amygdala, whose detailed learning formulas are given in [13], [16].

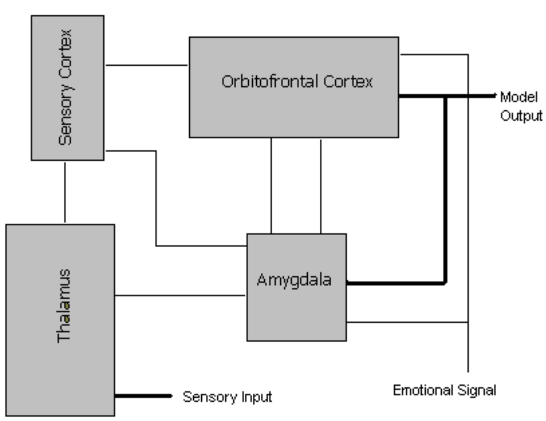

Fig.2 Schematic structure of BELBIC controller

The results derived from using BELBIC in controlling many different plants in [13], [14], and [15], prove its extravagant ability to give us truly satisfactory control actions.

4 Implementation and Simulation Results

As mentioned earlier, systems include BELBIC have shown considerable robustness and fast responses. In this section, we have adopted the BELBIC structure, which was introduced in [13], but with delay elements, represented in [14], in order to reduce the effects of the non-minimum-phase behavior. Of course, the delays were tuned without any prior knowledge to the plant elements, and they merely help distribute reward, dynamically without attempting to find the optimal credit assignment schema. The biological plausibility of this modification stems from the fact that delayed signal passing have been known to occur in orbitofrontal and sensory cortex [16].

First we tried to apply separate BELBIC blocks to each plant input in feed forward loop of the system so that the input signals have the proper interpretations. The structure we used in our first trial is illustrated in fig.3. The functions we used for emotional cue and sensory input blocks are as follows:

$$SI_{1,2} = W_1.PO_{1,2} + W_2.\dot{PO}_{1,2} \qquad (5)$$

$$EC_1 = W_3.e_1 + W_4.CO_1 + W_5.CO_2 \qquad (6)$$

$$EC_2 = W_6.e_2 + W_7.CO_1 + W_8.CO_2 \qquad (7)$$

Where EC_k, CO_k, SI_k and PO_k are k emotional cue, controller k output, k sensory input and plant k output, and W_1 through W_8 are the gains tuned for designing a satisfactory controller.

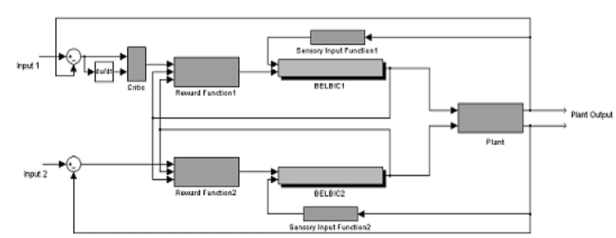

Fig.3 Control system configuration using BELBIC

In the mentioned figure there is a block named critic. We added this fuzzy block, which its structure and usage are introduced in [20] and [22], in order to improve the output behavior. The simulation results are shown in fig.4. As it can be seen, unlike vertical velocity, the altitude, which is supposed to behave like a simple ramp function, does not give satisfactory results. This is because of the fact that our MIMO system is strongly coupled, so two separate BELBIC blocks are not able to control both parameters simultaneously.

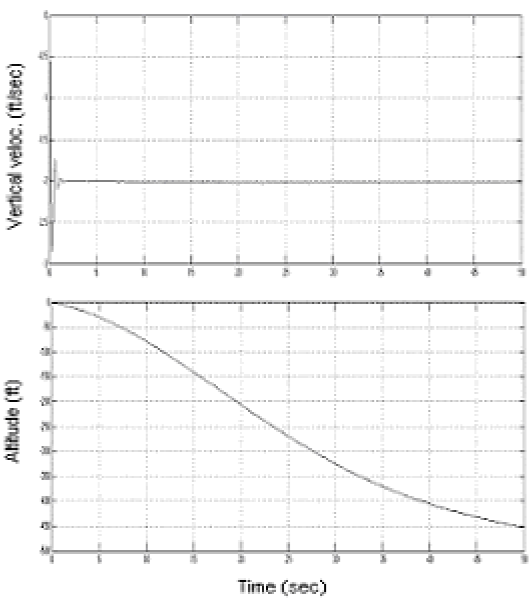

Fig.4 Aircraft response during landing in the absence of wind shear with two BELBIC blocks

In order to prevent such non-acceptable results, we decided to use one BELBIC block and OWA method, introduced in [21]. Our new schematic structure is illustrated in fig.5. Although the controller outputs are the same, BELBIC is able to achieve desirable characteristics as its output is chosen by ordered weight averaging. We also added some factors to reward functions, which are described below, to get satisfactory results.

$$EC_1 = W_1.e_1 + W_2.\frac{d}{dt}e_1 + W_3.CO_1 \tag{8}$$

$$EC_2 = W_4.e_2 + W_5.\frac{d}{dt}e_2 + W_6.\int e_2 + W_7.CO_2 \tag{9}$$

$$SI_{1,2} = W_{8,9}.PO_{1,2} + W_{10,11}.\frac{d}{dt}PO_{1,2} \tag{10}$$

Where EC_k, CO_k, SI_k and PO_k are k emotional cue, controller k output, k sensory input and plant k output, and W_1 through W_{11} are the gains tuned for designing a satisfactory controller.

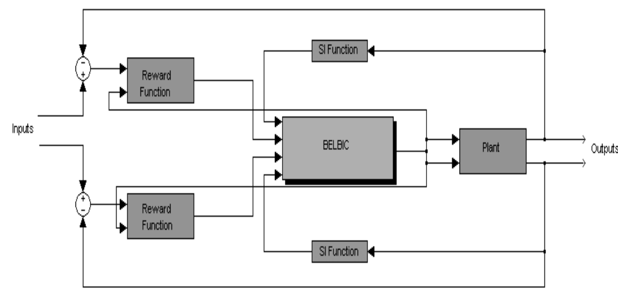

Fig.5 Controller circuit with one controller (BELBIC block includes the OWA element.)

From now on, our work is about presenting the simulation results in the absence and presence of wind shear disturbance. We decided to compare our results with the results derived from using high-gain method so that we would be able to prove our controller's fine functionality. The output signals are visualized in Fig.6. A brief look at figure 6-d proves that high-gain controller is not able to satisfy design objectives, as the overshoot exceeds proper limitations. It is also observable in 6-g that while using BELBIC controller the output signals stay in desirable range, even in the presence of wind shear disturbance.

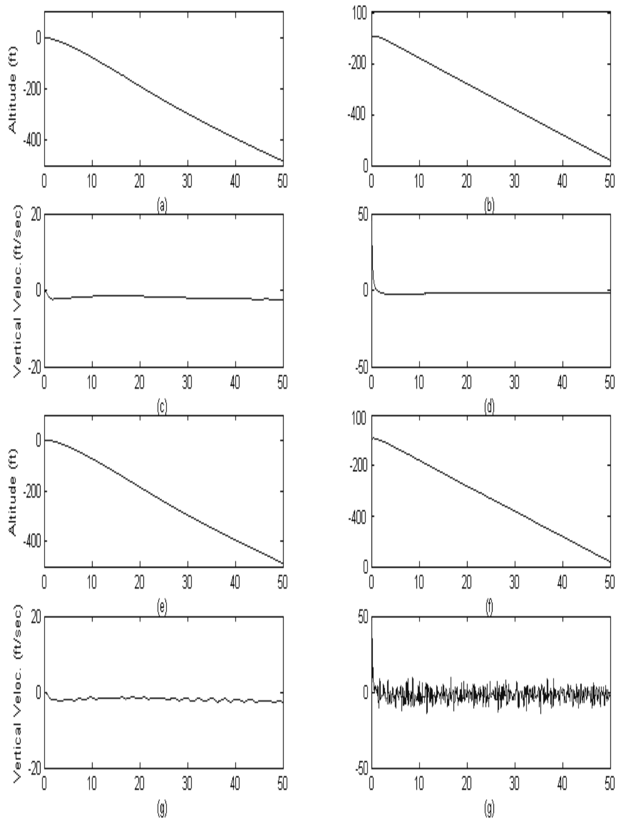

Fig.6 Simulation results, BELBIC controller results are represented in left column as well as high-gain controller in right column. (Figure 6-e to 6-g plot output signals in the presence of wind shear.)

5 Conclusion

In this paper, we proved the capability of an intelligent controller, BELBIC, which is based on a model of mammalian emotional learning, in satisfying autolanding system objectives. We also showed that our innovative controller, unlike high-gain controller, which is a classic one, is able to handle wind shear disturbance, as it maintains in permitted range. It is also believed that an optimal tuning in emotional cue block constants would help us to achieve even better responses.

Appendix

$$X_u = -.038, Z_u = 0.0313, M_u = 0.0211$$

$$X_w = -.0513, Z_w = -.605, M_w = 0.157$$

$$X_q = 0.00152, Z_q = -0.410, M_q = -0.612$$

$$X_E = 0.00005, Z_E = -0.146, M_E = 0.459$$

$$X_T = 0.158, Z_T = 0.031, M_T = 0.0543$$

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