Modeling of the Visual Approach to Landing Using Neural Networks and Fuzzy Supervisory Control☆

Jorg Onno Entzinger, Shinji Suzuki

University of Tokyo, School of Engineering, Department of Aeronautics & Astronautics, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan

Abstract

During the visual approach to landing of a fixed wing aircraft, a human pilot bases control and timing of subsequent maneuvers mainly on the out-the-window view, as there is not sufficient time to read all instruments. The skill of making smooth and soft landings is acquired mainly through experience. Research has been done to identify the most important features in the visual scene (cues) for two phases of the visual approach to landing: glide slope tracking and the flare maneuver. Using simulator and real flight data, neural networks have been trained for both phases to mimic the pilot's control based on the visual cues available. By using the γ operator in neuron transfer functions, a transparent model is obtained. Fuzzy supervisory control is proposed to couple the networks and thus provide insight in the pilot's decision making process with respect to timing the flare initiation.

Key words: Pilot modeling, aircraft landing, visual perception, neural networks, fuzzy logic

1. Introduction

The visual approach to landing is generally considered one of the most demanding phases in human pilot control [1]. The combination of high workload, having to interpret the visual scene, timing the initiation of subsequent maneuvers and executing those maneuvers, all with the risks inherent to low-altitude flight, makes this process difficult to learn for new pilots. Real and/or simulated experience is indispensable to obtain and maintain landing skills, and performance feedback is thought to greatly improve learning efficiency [1, 2]. However, most pilots cannot explain what they look at or how they make their decisions and even training methods are not consistent.

The research presented in this paper focuses on finding the visual cues a pilot uses, through analysis of scene and flight control data. A method is presented to construct a model of a human pilot which takes visual cues and generates longitudinal control actions during the visual approach to landing. This model is based on numerical data from real or simulated landings by human pilots. The model itself however is merely used to verify correspondence between the real pilot and the model. Of main interest are the structure and parameters of the resulting model, i.e., the driving inputs, internal relations and thresholds, as these give insight in the pilot's (subconscious) behavior.

The knowledge gained from this "reconstruction of the pilot's mind" would be useful in training or evaluation of pilots: if we know how experienced pilots use the available visual cues to make smooth and soft landings, these insights can be taught to trainees. Comparison of behavior between pilots could be helpful to give specific feedback to improve one's performance. It can also help finding out why and when optical illusions arise and how pilots can be trained to recognize or avoid them. Direct application of this knowledge to automatic landing systems may not be meaningful, since accurate state information is abundant within the flight computer, and image processing may not be sufficiently robust to meet safety requirements. Such automatic landing systems could however prove useful for small unmanned aerial vehicles (UAVs) [3] —which have limited positional and state information due to payload restrictions— provided the availability of a camera and microprocessor (which might be on board for specific mission goals anyway). Apart from pilot training and UAV landing systems, there is a wide application for the knowledge of which visual cues pilots use, ranging from cockpit display design and human-machine interaction studies, to enhancing the realism of the important cues in flight simulators.

2. Visual Perception during Landing

Some of the earliest studies on the visual perception for vehicular guidance[1] are those on ego-motion and motion perspective (optical flow) by Gibson et al. [4] and Gordon [5] in the 1950s and '60s. Since then several researchers have investigated the way pilots look at the out-the-window scene and a wide variety of visual cues has been suggested for guidance during the final approach to landing.

☆This work has previously been presented at the ICAS 2008 Conference (`http://www.icas.org/`)

Email address: `Jorg@Entzinger.nl` (Jorg Onno Entzinger)
URL: `http://Jorg.Entzinger.nl` (Jorg Onno Entzinger)

[1]The problem discussed in this paper is closely related to that of car driving, a skill which is also learned through experience.

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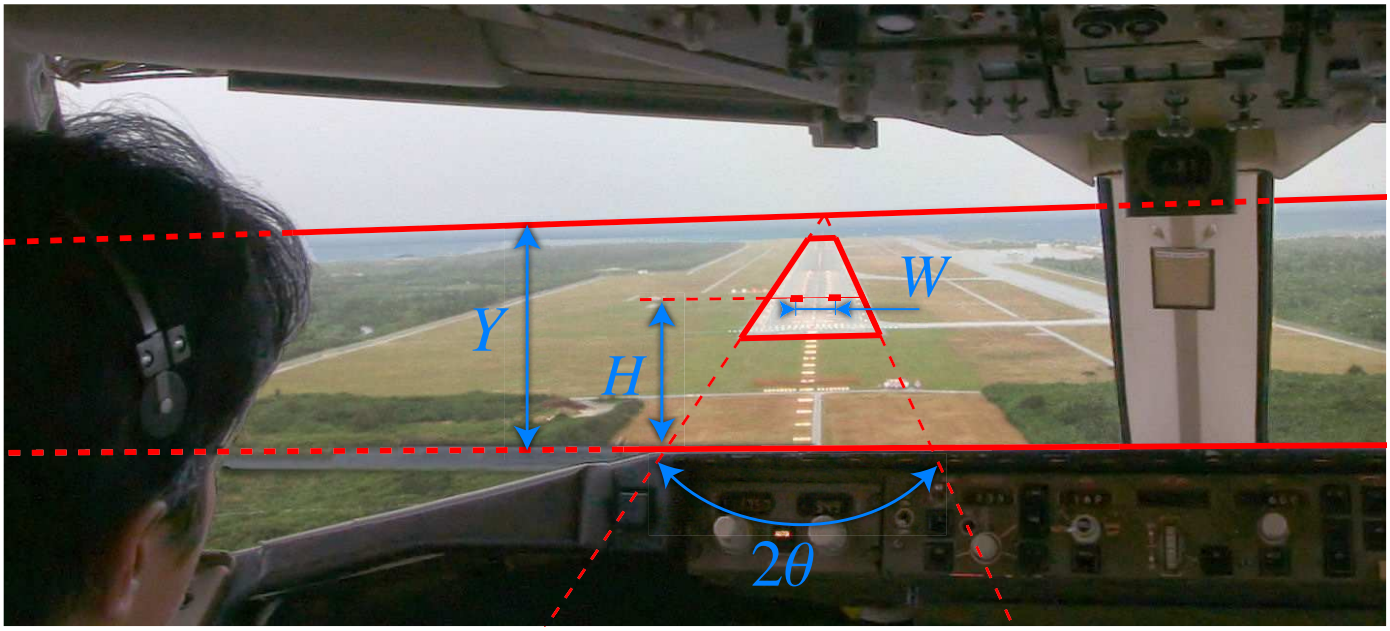

Figure 1: Definition of visual cue variables. Y and H are the vertical positions of the horizon and the touch down zone markings (TDZM) relative to a fixed location in the aircraft. The implicit horizon is therefore defined by $Y - H$. W is the apparent distance between the TDZM, and thus a cue for distance. θ is the apparent inclination of the runway edge, an altitude cue. τ_θ will be defined as $\theta/\dot{\theta}$, with $\dot{\theta}$ the time derivative of θ.

Apart from general cues such as optical edge- and flow rate and texture [6–8], the 'implicit horizon' (distance between the horizon and the aim point, measured in the visual plane; Y-H in Fig.1) is often mentioned as an important cue [9–12], especially for keeping the preferred glide slope. The position of the horizon (Y) is known to have a close relation to the pitch of the aircraft. The runway shape in general (also referred to as perspective), or specific cues like the perceived inclination angle of the runway edges (splay; θ) and the apparent length or width of the runway are also mentioned in literature, but there is no consensus about their use [2, 9, 11, 13].

Another controversial cue is τ, the time to contact as defined by Lee [14], which can be derived from the optical flow or from a specific feature such as the apparent runway width. τ has been suggested as a guide for the flare phase (roundout) [2, 15], although others [16] could not confirm this and found a dependency on sink rate instead (which is consistent with [17], but sink rate is not a readily available visual cue).

This quick overview of possible cues shows that there are many visual cues available to the pilot and for most of these cues, taking the time derivative of the cue into account could also be meaningful. Figure 1 shows an overview of the cues considered in this research. It must be kept in mind that the usage of cues varies through the phases of the landing [18], and that some cues are used as a trigger to commence a new phase.

3. The Final Approach to Landing

The final approach to landing can be divided into two phases. In the first phase the pilot should maintain a constant descent which is generally about 3 degrees and keep the airplane aligned with the runway centerline. This phase will be referred to as the 'glide'. The second phase is the 'flare' (also called roundout), where the pilot slowly pulls the column to make the aircraft pitch up in order to decrease the sink rate and land on the main landing gear first before the nose gear (Fig. 2).

Proper timing and execution of the flare are critical for a soft and safe landing. *The rate at which the roundout is executed depends on the airplane's height above the ground, the rate of descent, and the pitch attitude. A roundout started excessively high must be executed more slowly than one from a lower height to allow the airplane to descend to the ground while the proper landing attitude is being established. The rate of rounding out must also be proportionate to the rate of closure with the ground. When the airplane appears to be descending very slowly, the increase in pitch attitude must be made at a correspondingly slow rate. [12]*

4. Data Acquisition

To find the cues a pilot is using when landing an airplane, a relation is sought between the available cues and the pilot's control. The current investigation only considers longitudinal motion (i.e., motion in the vertical plane) which limits the pilot control inputs to throttle setting and column deflection. As the throttle setting is normally[2] kept constant and only set to idle at

[2] It should be mentioned that in simulated landings of a Dornier Do228-202 propeller airplane, some flares appeared to be performed by slowly decreasing the throttle, while column deflections were minimal (see Fig.5). In the experiments with jet aircraft this behavior has not been observed.

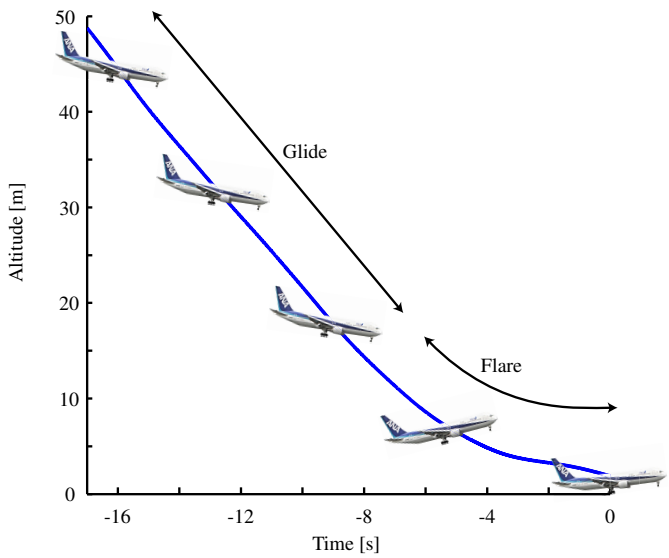

Figure 2: In the final approach to landing, the pilot pitches up to arrest sink rate and land softly on the main gear. This maneuver is called the flare.

the end of the flare, the control column deflection is the main source of pilot response data.

4.1. Simulated Landings

From the simulated landings the main aircraft states (position, velocities, attitude, rotational speeds, control surface settings) and the column deflection and throttle setting were obtained. Knowing the simulated airport geometry, the states are translated into visual cues as they would be seen through the cockpit window.

Landing data has been obtained in several sessions using:

- A simple parabolic screen simulator with a Boeing 767 model and an abstract scene (no texturing and a simple airfield geometry) [@50Hz] However, the hardware allowed only coarsely discretized column deflection data to be obtained.

- A high class simulator with Wide Angle Collimated display owned by JAXA (Japan Aerospace Exploration Agency) [Dornier Do228-202 propeller airplane @20Hz]

The simulators were always operated by experienced pilots holding a license to fly the real plane.

4.2. Real Landings

During a few real ladings of a Cessna Citation data were gathered using 2 video cameras installed in the cockpit (Fig. 4). One records the out-the-window view, the other camera is capturing the column movements from the side (@30Hz). A marker is put on the column to simplify video post-processing and extracting numerical column deflection values. The images of the out-the-window view are also post-processed to obtain numerical values for the selected cues.

Figure 3: The JAXA owned flight simulator used with the Dornier Do228-202 propeller airplane model and scene with rich texture.

5. Proposed Modeling Method

The cues used are strongly influenced by the task, the availability of other cues, the experiment setup and also on a pilot's experience or even preference. Identification of the cues which contribute most to the pilot's control is therefore a major part of the proposed assessment.

First the proposed modeling techniques are introduced, after which the application of those techniques to the human pilot modeling problem will be explained in the second subsection.

5.1. Modeling Techniques

The crossover or optimal control models from the 1960s [19, 20] are still the base for most of the proposed pilot models [21–23]. This classical control theory approach has some limitations. One important limitation is that it assumes a linear feedback loop, which may be no problem for modeling a (laboratory) tracking or pursuit task, but a more general model is needed for a complex maneuver like the flare, where multiple (visual) inputs, visibility thresholds and saturation, and multiple control objectives (sink rate, touch-down point, final pitch attitude) play a role. Another important limitation of the classical control models is that they are highly mathematical and therefore ill suited for explaining human functioning in normal

Figure 4: The control command is recorded using a white cross marker on the column (left), the visual cues are recorded with the camera on the right.

linguistic terms, which is essential when they are to be used for evaluating pilot strategies and for generating feedback to pilots.

The use of fuzzy logic and neural networks (NNs) is considered because of their close correspondence to human functioning and their generality and flexibility. As the main interest lies in the structure of the model, it is important to choose a model with high transparency, which is often a problem with NNs. To obtain a transparent network which can still be trained from data, the γ-model proposed by Zimmermann and Zysno [24] is used as a transfer function in a NN framework. The 'γ-network' and training procedure as described by Krishnapuram and Lee [25]] was implemented.

The neuron transfer function $y = f(x_1 \dots x_N)$, which is usually the sigmoid function, is in this research defined using the γ-model:

$$y = \left(\prod_{i=1}^{N} x_i^{\delta_i} \right)^{1-\gamma} \left(1 - \prod_{i=1}^{N} (1 - x_i)^{\delta_i} \right)^{\gamma} \tag{1}$$

with:

$$x_i, \gamma \in [0, 1] \quad \text{and} \quad \sum_{i=1}^{N} \delta_i = N$$

Parameters γ and δ can be trained using error back propagation algorithms [25], similar to the training of biases and weights in standard NNs.

The left part in (1), which is raised to the power $1 - \gamma$, represents an 'AND' connection between the inputs x_i, each weighed by its respective δ_i. The right part, raised to the power γ, represents an 'OR' connection. By adjusting the value of γ a *weighted combination of the non-compensatory 'AND' and the fully compensatory 'OR' [24]* is obtained. Such partially compensatory behavior is often found in human actions. Another strong point is that the proper values of γ can be obtained from the NN learning process, so no presumptions have to be made about the 'AND' or 'OR' structure of the model.

For the transition from glide to flare phase, a fuzzy supervisor is proposed. This high level controller basically models the pilot's decision making process with the possibility of a gradual instead of an abrupt change of control style. It takes the visual cues as an input and decides whether the glide model, the flare model, or a combination of outputs is appropriate.

5.2. Modeling Process

The modeling process can be split into 4 steps:

Step 1. **Splitting data into glide and flare phase data.** The landing data is manually split into data for each phase by close observation of the time histories. Especially the column data, climb rate, horizon and change of horizon are considered. Explorative studies on separation by fuzzy clustering have been done, but robustness against unrelated input variables and accuracy are still issues.

Step 2. **Cue identification/modeling of each phase.** For each phase, a γ-network is trained using the (normalized) cue data as inputs and the corresponding column deflection as output. The weights and structure of the resulting networks show which cues are used and how they are used.

Step 3. **Identification of the visual cues used for phase transition.** This is similar to step 2, but using the full data set (i.e., both glide and flare data) as input and an output which is high in the few seconds preluding the flare initiation.

Step 4. **Determination of the fuzzy supervisory control parameters.** Based on the results of step 3, a high level fuzzy controller is designed to adjust the contribution of the phase-specific network outputs to the control. This step integrates the models and knowledge obtained in the previous steps and is considered mainly for verification purposes.

6. Results

First one landing analysis case will be highlighted to illustrate how information can be derived from the obtained data and models. After that, the second subsection presents a short overview of results obtained from the other data sets.

6.1. A 'Typical' Landing Case

[The flare] should be a continuous process until the airplane touches down on the ground [...] back-elevator pressure should be gradually applied to slowly increase the pitch attitude and angle of attack [...] power normally is reduced to idle during the roundout [...] This will cause lift to decrease again, and it must be controlled by raising the nose and further increasing the angle of attack. [12] The green line in Fig.5 shows such a landing, where the column is pulled gradually (then released gradually to prevent a too high pitch at landing) and when the throttle is set to idle, the column is pulled again slightly.

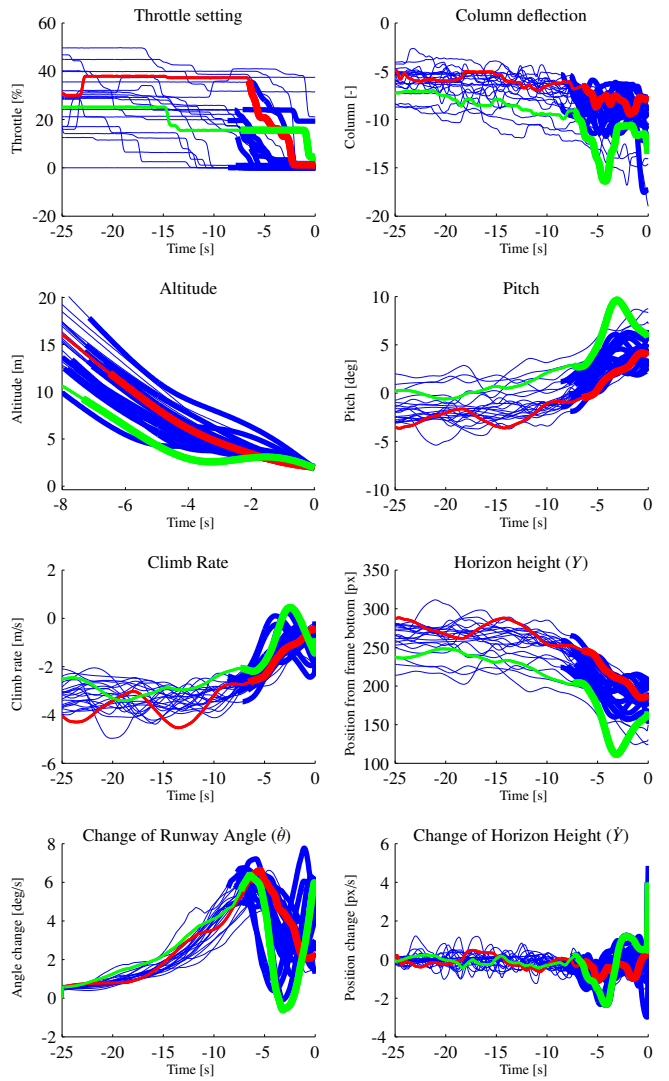

Figure 5: In the landings carried out in the Dornier Turboprop simulator several different control strategies appeared to be used. The thick part of each line corresponds to the flare phase. The green line shows a 'typical' landing, as described in the FAA Handbook [12]. The red line shows a strategy where the flare is mainly performed by decreasing the throttle.

The data has been separated into 'Glide' and 'Flare', which are distinguished by the thinner, respectively the thicker part of the lines in Fig. 5. For the typical case the column movement itself gives a clear indication of the timing of flare initiation, which is supported by the pitch, climb rate, horizon height and change of horizon height.

Figure 6 shows the trained γ-networks. Networks with only 2 hidden layer neurons proved sufficient; when adding a third hidden neuron, its contribution to the output layer neuron was always weighed virtually zero. The lower row of black rectangles in each of the 3 plots represents the inputs (cues) available to each network. These input values are propagated to the hidden layer neurons, where the γ-function is applied. The outputs of the hidden layer neurons are then propagated to the output neuron, where the γ-function is applied again to obtain the final output. The relative weights δ_i are represented by the widths of the connection lines, the values of γ are written next to the neurons. The small graphs at the left of each network show the original training data (black) and the network outputs (red). The upper 2 networks in Fig. 6 are the models obtained for the

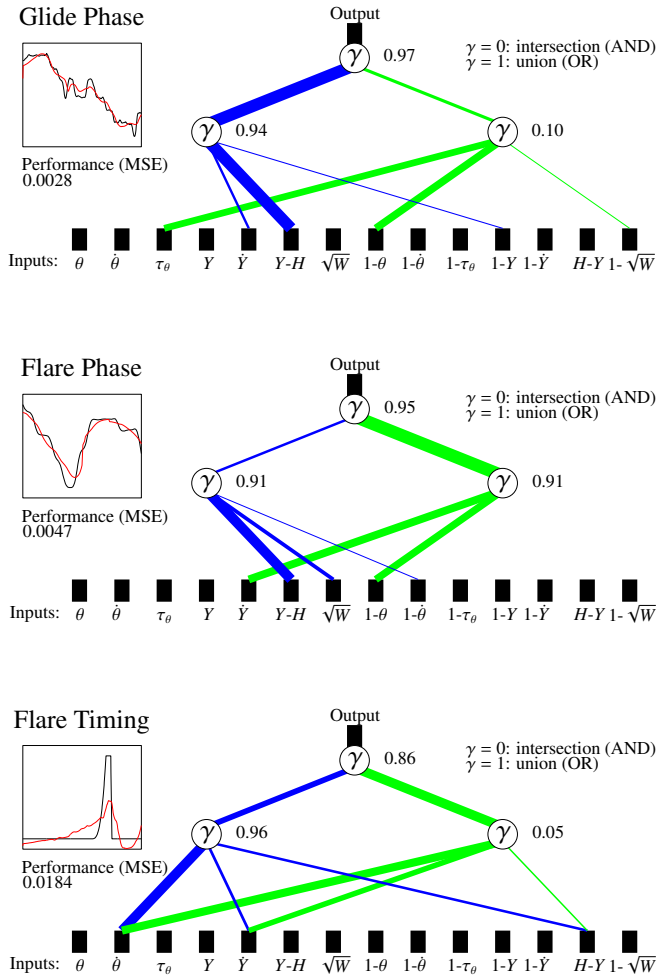

Figure 6: The result of identification of cues used by the pilot. From top to bottom for Glide phase, Flare phase and for timing of the Flare initiation. Thicker lines represent stronger weights. Note that all variables were normalized, so 1-θ is just the complement of θ.

glide and flare phase control. The lower one identifies the cues which trigger the flare initiation. If we look at the network for the glide, we see that there is a strong connection between input 'Y-H' (the implicit horizon), via the left hidden layer neuron to the output neuron at the top. The right hidden layer neuron reacts as 'τ_θ AND 1-θ' which corresponds to the general trend that the column deflection is small in the beginning (far away, so the time to contact is large and the runway angle is small) and slowly grows (the downward trend in Fig. 5, top-right). However, from the connection weights between the hidden layer and the top layer, it becomes clear that the implicit horizon is the main cue for glide control.

When looking at the flare network, we see the main cue is '$\dot{Y}$ OR 1-θ'. The use of $\dot{Y}$ indicates feed forward control during the flare, while the '1-θ' —'pull up (large column deflection) when θ is high (altitude is low)'— is modeling the pilot's final pull

of the column, which comes with the decrease of throttle. The contribution of the implicit horizon via the left hidden neuron can be explained by the fact that halfway through the flare, the touchdown zone markers disappear from sight, thus saturating the value of Y-H. This event may be a cue for the longitudinal position with respect to the runway. In the model, the influence of the high value of Y-H shows the pilot's gradual release of the column.

As discussed in §5.2 step 3, the cues likely to be used for timing of the flare initiation are identified in the same way as for glide and flare control. The lower network in Fig. 6 shows the result. It is clear that $\dot{\theta}$ (change of angle between the runway edges) is the dominant variable. The right neuron states '$\dot{\theta}$ AND $\dot{Y}$'. The 'AND $\dot{Y}$' part is merely an artifact to ensure the model output is low again during the flare, as $\dot{Y}$ is low during the flare. The appearance of $\dot{Y}$ in the result is thus not due to its importance for flare initiation timing, but just stresses that it is the part *preluding* the flare that we are interested in.

To determine the parameters of the fuzzy supervisor, the data has been split into 2 sets using Fuzzy c-means clustering (see [26], App. I for a clear algorithmic description). As the time derivatives of θ and Y were identified as important for flare timing in the previous modeling step, θ and Y will have relatively large change of value during the transition, and are thus suitable to base the clustering on. Figure 7 shows the clustering result. The plot of the column deflection is shown as a reference, it was not used for clustering. This result shows that good separation can be obtained this way, which verifies the function of $\dot{\theta}$ and $\dot{Y}$ as cues for flare timing.

For further verification purposes the Glide and Flare networks could be integrated using a fuzzy supervisor based on the membership function resulting from the clustering procedure described above. Figure 8 shows the resulting model output and the original column output as reference.

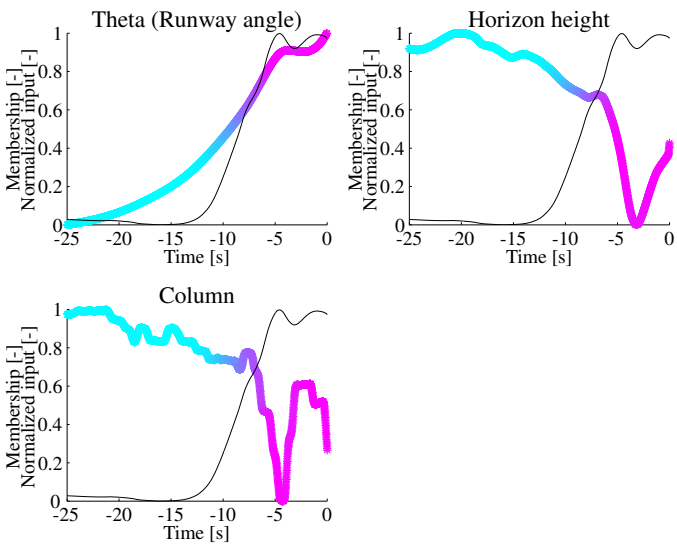

Figure 7: Two classes, Glide (cyan) and Flare (magenta), were separated using fuzzy clustering. The black line shows the degree of membership to class 'Flare' for each sample.

6.2. General Results

Many landing approaches were analyzed. In general the implicit horizon and time to contact are the main cues during glide, often supported by a 'distance cue' such as the (change of) runway angle or distance between the markers.

For flare timing the change of runway angle appears to be very important, but in many flights the value of the implicit horizon seems to play a major role. Especially in the Parabolic screen 767 simulator landings several 'ballooned flares'[3] were flown, all of which had a value for the implicit horizon clearly lower than normal flares at the time of flare initiation.

The control during the flare proved the most difficult to model. Results vary widely, however it should be noted that characteristics of human control also vary widely: from the 'typical' flare (Fig.5, green line), via strongly alternating column movements, to throttle-controlled flares with minimal column movement (Fig.5, red line).

In the real flight experiments the time to contact was shown to be closely related to the control. In the simulations, rather than this $\tau_\theta(=\theta/\dot{\theta})$, the separate parameters θ and $\dot{\theta}$ (the apparent angle between runway edges and its time derivative) were often found to guide flare control. Also the position and movement of the horizon were found as cues.

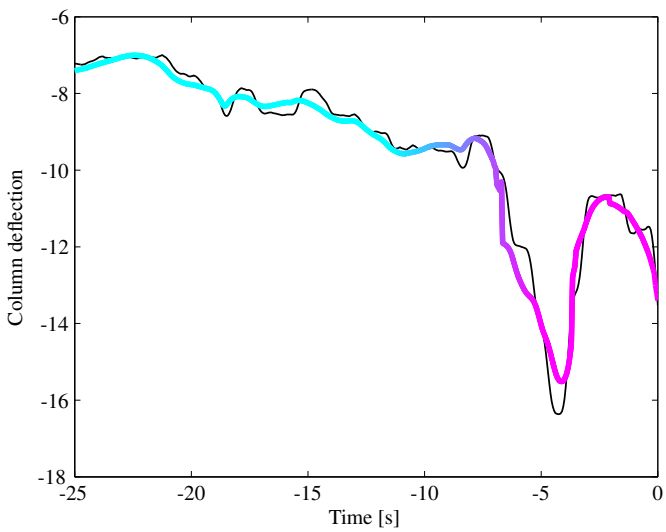

Figure 8: Column deflection output of the integrated model. The black line is the original pilot control.

7. Discussion

The result that the implicit horizon plays an important role in glide is supported by literature as mentioned in §2. The finding that τ_θ also seems to play a (secondary) role is interesting, however it should be investigated whether the changes of this cue are big enough to be perceived from such distance.

[3] A too strong pitch up such that not only sink rate is deceased, but the airplane actually starts to gain altitude.

The importance of the change of runway angle for the timing of the flare initiation is remarkable, as no previous notion of this was found in literature. As $\dot{\theta}$ contains combined information on the altitude and the sink rate[4], it is considered a very reasonable cue for flare timing.

Because of this result, the time histories of $\dot{\theta}$ and the column deflection have been investigated closer. It is interesting to note that $\dot{\theta}$ reaches nearly the same maximum value for each flight in the same simulated environment (Fig. 9). Figure 9 also illustrates the general finding that (for the typical landing style) the pilot starts pulling the column shortly before this maximum (marked ① in the figure)[5]. However, this first pull of the column is slight, slow and generally the pilot holds the column or even releases it shortly before really flaring (from point ② on). This start of the real flare is found to coincide with the maximum value of $\dot{\theta}$. It seems the pilot notices $\dot{\theta}$ increasing rapidly, slowing down this process by 'pre-flaring', and when $\dot{\theta}$ reaches the right rate of angle increase, the pilot fully flares the aircraft. Also of interest is the result that when the value of $\dot{\theta}$ gets too high again, the pilot commands some additional pitch just before touchdown (marked ⑤). This behavior has not only been found in the Dornier turboprop simulated landings, but also in landings recently carried out in a certified Boeing 767 training simulator.

Several pilots participating in the experiments also mentioned that the runway edge is important for flare timing. Although they say it is to estimate the altitude, no pilot can express this altitude in feet or meters. Taking into account that the altitudes at flare initiation vary widely, it is argued that these experienced pilots do know where to look, but may not be aware of the complexity of the perceived information.

As aircraft state data were available for the simulator landings, a superficial analysis has been performed using the proposed modeling method with these states as inputs. An interesting result from the 767 simulator analysis is that a combination of altitude and sink rate is found for timing of the flare. For the Dornier landings, a combination of the altitude and time to contact τ_z (altitude/sink rate) were often identified. Both results confirm the findings of Grosz et al. [16] that not exactly τ_z, but still some combination of altitude and sink rate determines the flare timing.

8. Conclusion

The presented approach can reveal which visual cues a human pilot is using in the visual approach to landing. As landing skills are obtained through experience and pilots often can't explain 'how' they fly, this information is valuable for trainee pilots who have not acquired enough skill yet. However, this knowledge also has various other applications such as the development of cockpit instruments, scene enhancement in bad weather approaches and improvement of simulator fidelity.

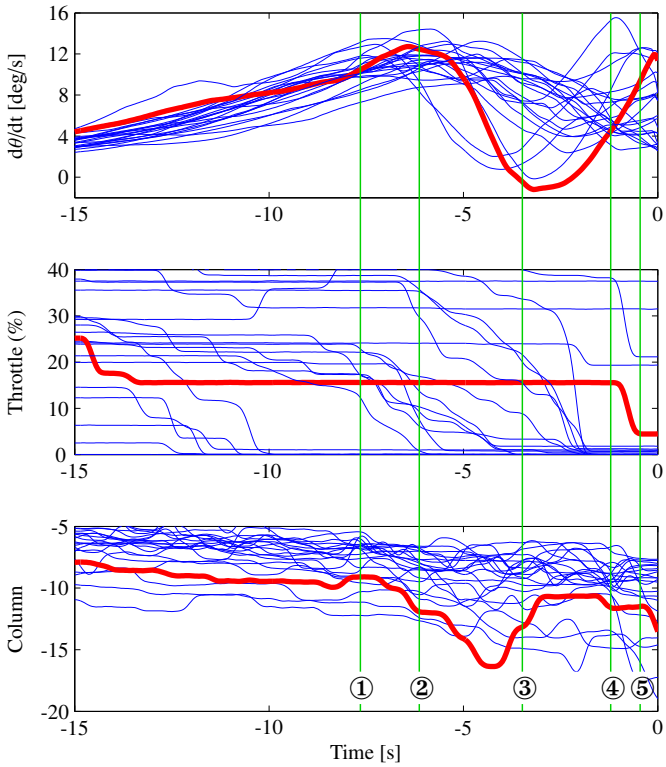

Figure 9: The proposed visual cue $\dot{\theta}$=dθ/dt is shown in the upper figure, and seems to reach a constant maximum value of ca. 12°/s regardless of flare control style ('typical' or 'by throttle', cf. Fig.5). ① start of 'pre-flare' ② pilot hesitates, seems to wait for/confirm proper cue value before fully flaring ③ pilot hesitates, seems to wait for/confirm no sink ④ when decreasing throttle, pilot compensates resulting pitch change ⑤ when cue value gets (too) high again, the pilot starts to pull the column more.

Rather than abstract mathematical models or black-box modeling approaches, a network employing the γ-operator was used, which resulted in transparent models which could easily be explained in natural language. Fuzzy clustering validated the cues found to be important for the timing of the flare initiation.

The use of the implicit horizon as a cue for maintaining the desired glide slope, which is commonly agreed on in literature, is supported, as is the influence of both altitude and sink rate on the flare timing. The most interesting result is that the change of the apparent angle between the runway edges was identified as the main cue for flare timing.

9. Future Works

The key to constructing effective models to capture human pilot behavior in terms of vision based decision making and control, is to know which cues are used. Further identification of possible cues, representing them in suitable numerical variables, and knowing the limitations of the human visual system with respect to these cues is considered of great importance.

[4]The apparent angle between the runway sidelines can be expressed as $\theta = 2 \cdot \tan^{-1}\left(\frac{\frac{1}{2}\text{Width}}{\text{Altitude}}\right)$, where "Width" stands for the real runway width (e.g. in meters). The time-derivative of this cue is a function of both altitude and sink rate: $\dot{\theta} = \frac{\text{Width}}{\text{Altitude}^2+\left(\frac{1}{2}\text{Width}\right)^2} \cdot \text{Sink rate}$.

[5]The initiation of this 'pre-flare' varies considerably in time, value of $\dot{\theta}$, and indeed also in all the other observed cues and states.

Once this information is available, data mining or modeling such as the proposed method can reveal which cues are actually used and how. Future works are therefore considered in the field that connects aeronautics and psychophysics.

In recent discussions experienced Boeing 767 pilots stated that the flare timing, and especially the moment of setting the throttle to idle depends on the head- or tailwind. Although junior pilots may flare at a more or less 'fixed altitude' as this is easy to learn (using Radio Altitude call-outs), experienced pilots perceive the right moment and thus have a more sophisticated landing technique. Further investigation of this technique and differences between junior and experienced pilots are therefore also considered promising directions for future research.

10. Acknowledgements

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