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東京大学
Paper 440 – Session 5.1.3

Modeling of the Visual Approach to Landing

Using Neural Networks and Fuzzy Supervisory Control

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(Feel free to contact me with comments/questions on this content; e-mail: jorg – at – entzinger – dot – nl)

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How to land an airplane?

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[video shows: 1) plane from outside; 2) cockpit window view; 3) control column deflection; 4) combined videos]

This shows the final approach to landing (last part of glide and flare)

The question is: what is the pilot looking at and how does he decide the proper control inputs

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Why do we want to know?

- Landing is the most difficult standard maneuver
- Major part of accidents in approach and landing
- Training efficiency
- Simulator effectiveness
- Instrument design
- Augmentation in bad visibility
- Awareness of visual illusions

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If we know how the pilot “sees” the aircraft motion and how he decides on his control, it will be easier to train new pilots, we can make more efficient and effective simulators, and it can help in understanding and recognizing visual illusions and thus increase air safety, etc. etc.

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How to land an airplane

(Visual) Perception (Aircraft) Control

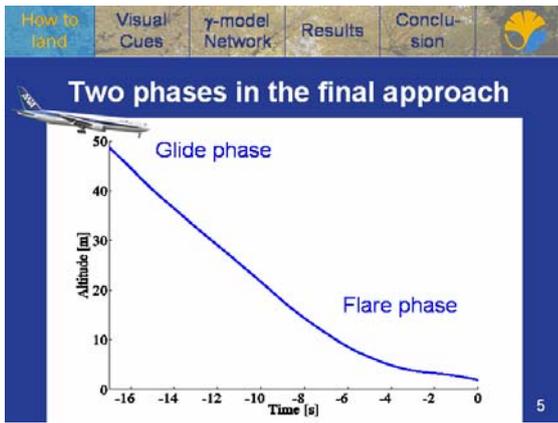
Filtering & Thresholding Cue selection State awareness Decision making Control

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The two main points in my research are PERCEPTION (how we sense the world around us) and CONTROL. These 2 themes contain several (conscious or subconscious) sub-stages when it comes to aircraft control by a human pilot.

- Some cues may be too small (or too big) to be visible, relative brightness or contrast levels may be insufficient, or cues may be dominated by other cues
- Some cues contain better/more/easier accessible information than others, the pilot is trained to use those cues and ignore others
- The pilot has a mental model of “what looks right” and what certain deviations of that “ideal image” mean (e.g. too high, too fast, ...)
- The pilot makes decisions to adjust, go-around, initiate flare etc
- The pilot continuously controls the aircraft according to the difference between perceived and desired state

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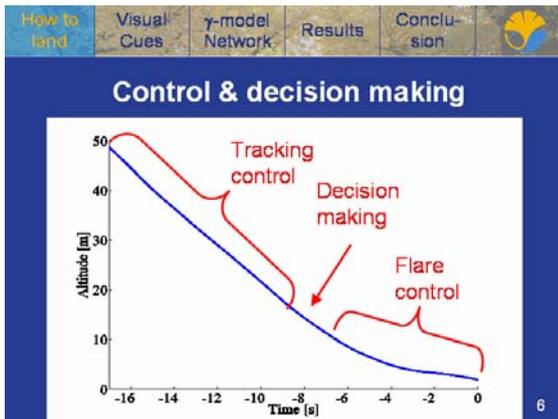
Currently I investigate 2 phases in the final approach to landing (if successful, maybe I add turn-to-final later)

[Animation]

- 1) The glide phase, where the pilot should track a straight path with about 3deg slope in the vertical plane
- 2) The flare phase, where the pilot should pitch up to reduce sink rate

The control in these phases is of a different style, so making separate models seems a good idea.

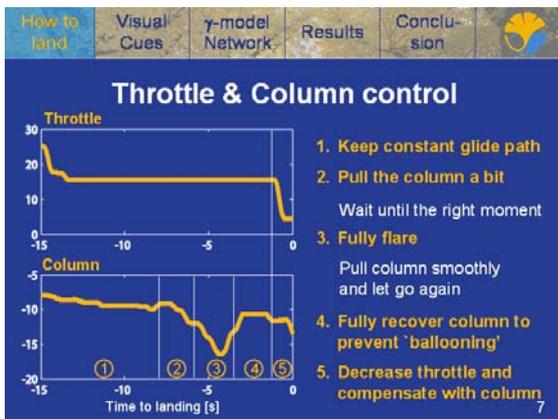
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In the glide the pilot has to maintain a constant descent. Therefore glide control is tracking control.

At some point the pilot has to start the flare. Based on the view from the window, he has to decide the right moment. Flare control is quite difficult to formulate. If the sinkrate is higher, the flare should be stronger; if the altitude is lower, it should also be stronger. Finally, the aircraft should have a certain pitch attitude to land on the main gear.

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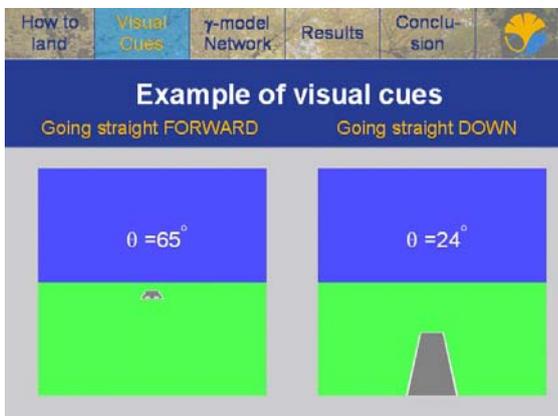
The main (longitudinal) controls are column (\rightarrow elevator \rightarrow pitch) and throttle (\rightarrow thrust).

This is a typical time-history of throttle setting and column deflection through the final approach and landing.

(for column: if the graph goes down, the pilot pulls the column, which results in pitch up)

As you see, the throttle is mostly constant and thus I focus on the column movement

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[videos] show how the scene changes when moving forward (left) or down (right) at CONSTANT speed

When moving forward, the shape of the runway is constant (the apparent angle between the side lines, theta, is constant). It only changes in size. When moving down, the shape changes (theta, gets bigger). Even at constant sinkrate, theta increases more than linear.

Actually, when moving DOWN at CONSTANT speed, the angle increases faster and faster. In the beginning you can almost not see the sideline rotating, but in the end it rotates very fast. Thus not only theta, but also the derivative of theta contains altitude information.

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

Overview of used cues

Additionally: $\frac{dY}{dt}, \frac{d\theta}{dt}, \tau_\theta = \frac{\theta}{d\theta/dt}$

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For longitudinal motion, there are many cues available to the pilot, these are the ones I use in this research. X is the “implicit horizon”. When maintaining a constant glide slope, with the markers as aim point, the “implicit horizon” is constant. This is thought to be an important cue for keeping the glide path.

X → glide slope

Y → pitch attitude ($dY \rightarrow$ pitch rate)

W → distance

Theta → altitude ($d\theta \rightarrow$ altitude, sink rate; $\tau_\theta \rightarrow$ time to contact)

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

Recording cues & control in real flight

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In the case of 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.

For data gathering during real landings, 2 video cameras were installed in the cockpit (see Fig). One records the out-the-window view, the other camera is capturing the column movements from the side. 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.

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

Other Pilot Models

Mostly:

- Crossover / optimal control models
- Neural network models

Drawbacks:

- (linear) feedback assumed
- Highly mathematical
- Mostly based on states, not on visual cues

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A review of literature shows that most pilot models are in terms of classical control theory, although some have applied neural networks.

I want a model that is flexible, general (glide, flare, ...), transparent (easy to explain what is happening to pilots and instructors), and above all, a model based on things the pilot is concerned with: visual cues, and not hard values of state variables.

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

Network model structure

Output (column position)

Inputs (Visual cues)

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To model a pilot’s control, I train a neuro-fuzzy network. The inputs are the (normalized) visual cues. Inputs at the left relate to “value is high”, inputs at the right (1-variable) relate to “value is low”. The output is the position of the control column. (a decreasing value means the pilot is pulling the column, an increasing value means he releases it)

Neural networks have a reputation of being black boxes. Using the gamma operator instead of a standard sigmoid function or so, the network becomes much more transparent and can be read in terms of logic reasoning [explanation of gamma operator on next slide]

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

γ-function

$\gamma : 0 \sim 1 \rightarrow \text{AND} \sim \text{OR}$ (Intersection \sim Union)
 δ : vector of neuron interconnection weights

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

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

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The gamma function, as a neuron transfer function, can assume AND, OR, or compensatory behavior. The left term, increasingly active when gamma approaches 0, takes the product of the inputs, weighed by delta. It thus forms the AND connective. The right term, increasingly active when gamma approaches 1, forms the OR connective.

In the neuro-fuzzy network structure, de values of gamma for each neuron, and the neuron interconnection weights delta can be trained like weights and biases in standard neural networks.

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Glide-phase control model

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For the glide phase the most important cue seems to be the implicit horizon. The connection between the chi input and the output has the strongest weights (thickest lines). This is what we expected from literature and as we saw in the animation in the beginning of this presentation.

Also a high time to contact AND a low runway angle has some minor influence, so while far away, the column position is “high” while the pilot pulls the column slightly during the glide

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Flare-phase control model

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In the flare phase the change of horizon OR the runway angle has the thickest line, and thus the strongest influence on the output. The change of horizon indicates feedforward control (increase pitch), while the the runway angle is important for the final pitch adjustment just before touchdown

During the flare, the implicit horizon OR marker width can be used as cues for distance; the aircraft should not “float” over the runway, but touchdown with enough runway left over for the rollout.

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How to land | Visual Cues | **γ-model Network** | Results | Conclusion

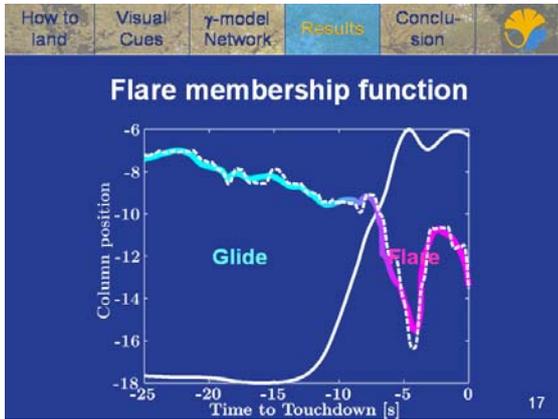
Flare timing model

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The timing of the flare appears to depend strongly on the change of the apparent runway angle. The “dtheta AND dY” actually only stresses that we are not talking about the flare itself, but the seconds precluding it.

As dtheta contains information about both altitude and sinkrate, it is actually not surprising this is a suitable cue. However is has never been clearly mentioned in literature, as far as I know.

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For verification of the results I discussed so far, I did the following test:
 For modeling, I separated glide and flare phases manually. Now we know that $d\theta$ and dY are high at the flare initiation. This means that the values of θ and Y must differ much between the glide and flare phases. Fuzzy Clustering gives this result. [solid white line is membership degree to flare phase]

When we use this resulting membership function (solid) as a supervisory controller to mix the outputs of the glide model and flare model, we see it indeed makes a very sensible cut, and the model output (colored) closely resembles the original column data (dashed)

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- Pilots can't tell which visual cues they use
- Training networks to mimic pilot control
- γ -function allows easy interpretation
 - *Glide*: Implicit horizon
 - *Flare*: Change of horizon OR Runway angle
 - *Timing*: Change of runway angle
- Fuzzy clustering to create a supervisor
- Verification by supervised model integration

Like car driving, the way to land an aircraft cannot be put into words easily. To find out what is happening (subconsciously) in a pilot's brain, I obtained visual cue and control data from real and simulated landings, and used it to make a neuro-fuzzy pilot model. Using the gamma operator, the network can represent AND or OR (or mixed) style logical connections, which makes it easy to understand the model.

Using the results of the Flare Timing Model, Fuzzy clustering of the relevant cues has shown to give a sensible result, thus verifying the relevance of these cues. The cluster membership was used as supervisory controller to combine the two lower level Glide and Flare network models.

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<p>(Visual) Perception</p> <ul style="list-style-type: none"> • How accurate can the change of Runway Angle ($d\theta$) be observed • Which other cues could be meaningful 	<p>(Aircraft) Control</p> <ul style="list-style-type: none"> • What type of control is used in each phase • What is good (optimal) control • How can a pilot's control be explained in words
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The two things I'm interested in are Perception and Control. I think on both subjects there is much research to be done. I like to work on both fields and try to combine them.

First priority is now to further investigate the "change of runway angle", which was found to be an important cue for flare timing. Visual cue research for flare timing is very sparse and $d\theta$ has never been reported as a timing cue in literature (as far as I know).

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Thank you
for your attention

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