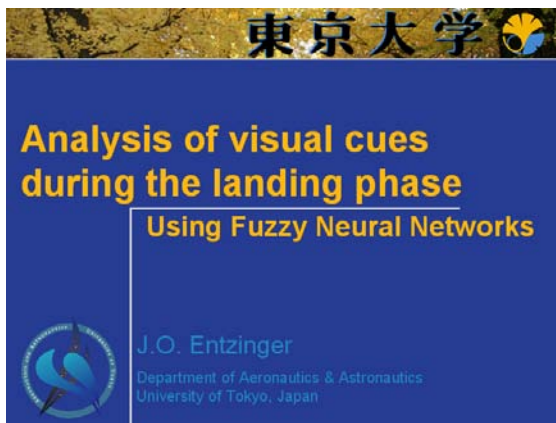


1



Presentation for WakeNet3-Europe Workshop

Berlin, 1-2 June 2010

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

For more information, please visit my website and download my PhD-Thesis or other papers.

2



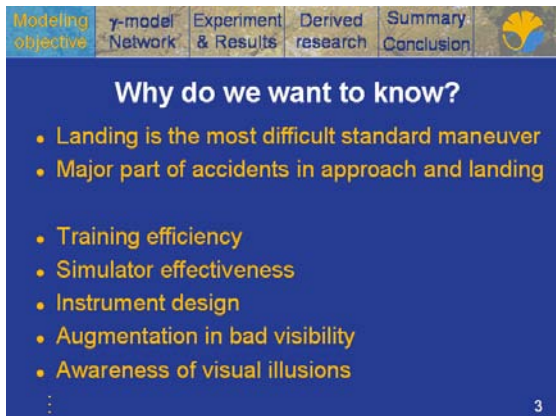
[video shows: 1) plane from outside; 2) cockpit window view; 3) control column deflection; 4) combined videos]

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

Focus: VISUAL

3



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.

The objective is NOT stability/handling qualities assessment
The model will NOT be used to control the aircraft in pilot-in-the-loop simulations etc.

>It is really to find out human reasoning and communicating subconscious behavior/techniques of experienced pilots to student pilots.

4



I investigated many different aspects of landing control through LITERATURE review, experiments, modeling, discussions with pilots etc.

1) The relative location of the aircraft with respect to the runway determines the visual scene

- I read many papers about visual cues, analyzed several cues mathematically etc.

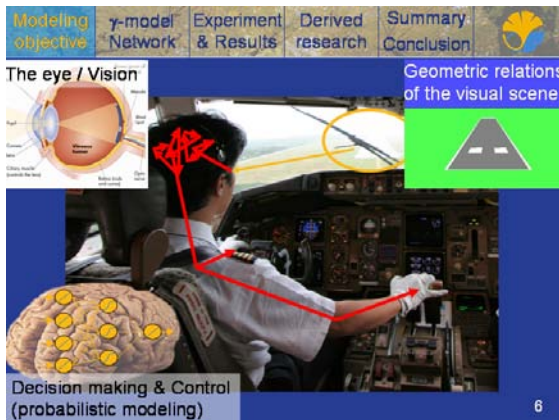
5



2) The pilot perceives the outside scene

- The human eye has its limitations. Tiny details or very slow movements may not be seen. I checked visibility thresholds for various cues, among which Binocular depth cues and Rotation of a line (segment)

6

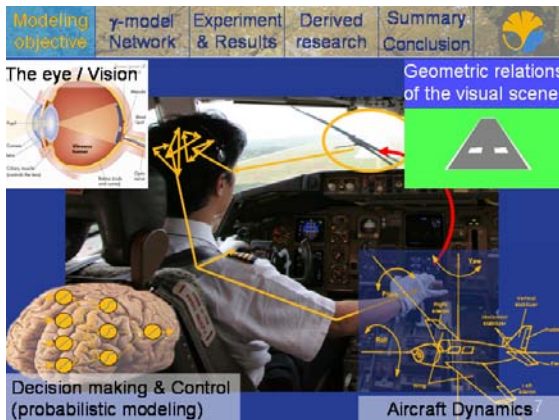


3) The pilot interprets the visual cues according to his mental model and takes actions/decisions

- I investigated classical and modern modeling techniques for human behavior

Main focus of my presentation at the WakeNet3-Europe Workshop (Berlin)

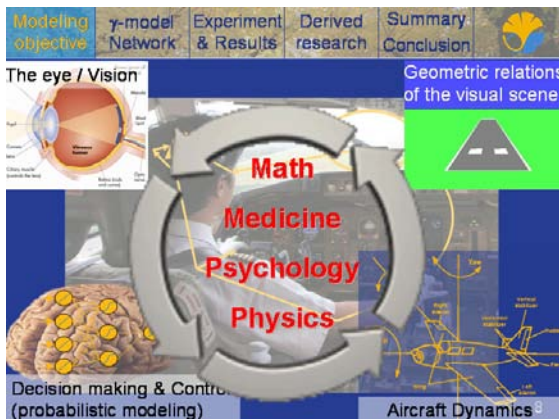
7



4) The aircraft responds to the pilot's control inputs and changes its path, thus changing the visual scene

- Since my background is in MECHANICAL ENGINEERING (control systems) I had to learn about aircraft dynamics and how control surfaces should be operated to change the flight path.

8

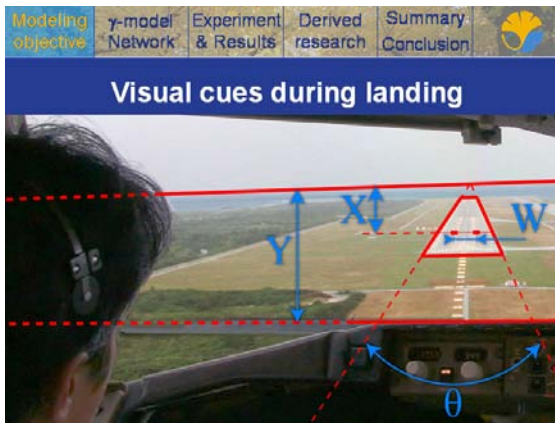


Landing the aircraft is a matter of closing the control loop
Scene → Perception → Decision making/control → Aircraft motion → Scene

I studied all aspects of the control loop

This means my research has become comprehensive and multidisciplinary

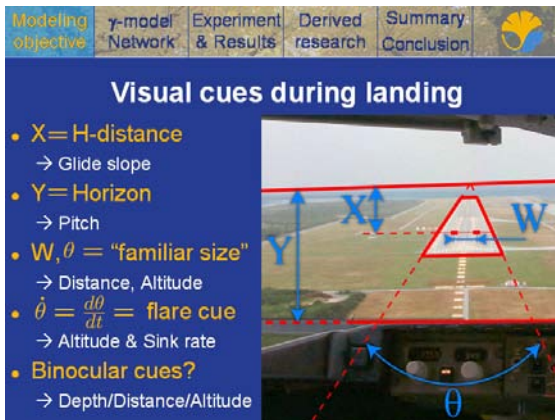
9



I will now explain some visual cues

There are many cues which a pilot might use. I just show a few simple ones here

10



The H-Distance is the distance between the horizon and the aimpoint. If you follow a straight line to the aim point, this distance will be constant.

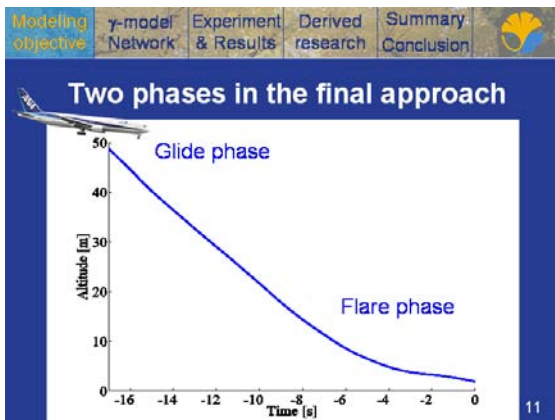
The distance from the bottom of the windshield (or any aircraft part for that matter) to the horizon provides information about the aircraft's pitch angle

Familiar size cues (also including the apparent size of trees, roads, buildings...) give distance information.

Stereoscopic cues could provide depth information, but for big aircraft it is probably not useful (for small aircraft and helicopters it might be)

I will focus on the flare (timing) cue $d\theta/dt$ now

11

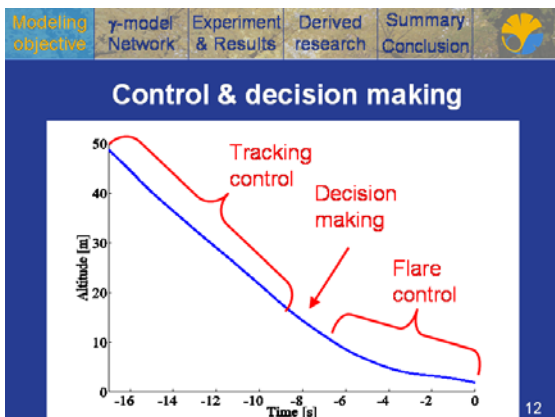


I investigated 2 phases in the final approach to landing [Animation]

- 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.

12



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.

Focus: VISUAL cues for DECISION MAKING

13

Modeling objective: **y-model** Network Experiment & Results Derived research Summary: Conclusion

Existing Pilot Models

Mostly:

- Crossover / optimal control models
- Neural network models

Limitations/Drawbacks:

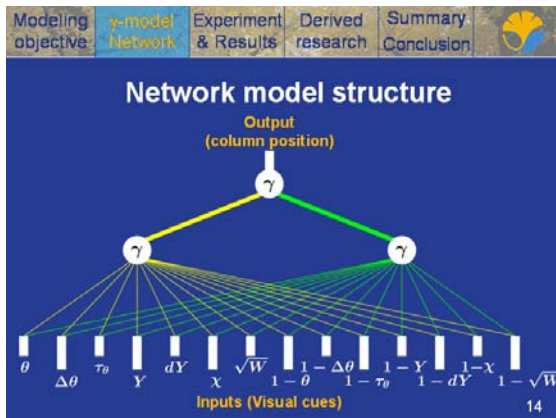
- (Linear) feedback assumed
- Highly mathematical abstractions (not transparent)
- Mostly based on states, not on visual cues
- Often based on instrument take off/approach

13

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.

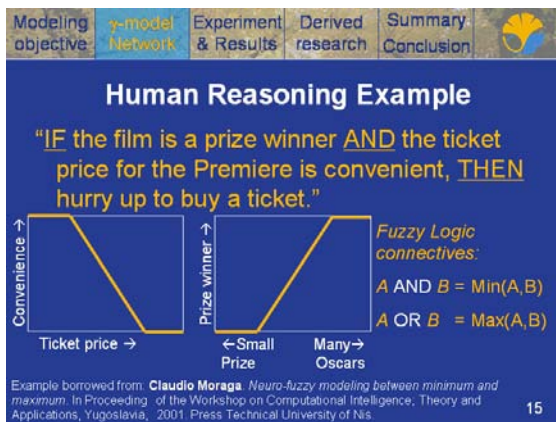
14



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)

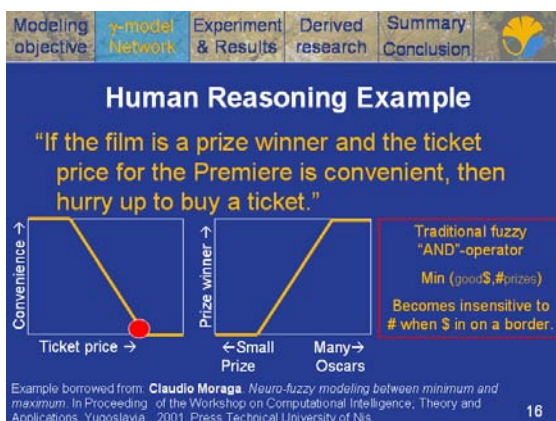
Neural networks have a reputation of being black boxes. Using the gamma operator instead of a standard sigmoid function or so, the network becomes much more transparent and can be read in terms of logic reasoning [explanation of gamma operator on the following slides]

15



This is how a decision rule (should I buy a ticket or not) is formulated in Fuzzy Logic. The premises are formulated as membership functions which typically show a degree of saturation.

16



The strange effect here is that the number of prizes doesn't matter anymore if the ticket price is on the border of what I think is acceptable to pay

In natural language, however, "AND" allows some degree of compensation. Surely, we are more willing to pay the exorbitant price for a multi-oscar winner, than for a low ranking movie.

17

Modeling objective	γ-model Network	Experiment & Results	Derived research	Summary Conclusion	
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γ- Operator

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

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

H.-J. Zimmermann and P. Zysno. Latent connectives in human decision making. Fuzzy Sets and Systems, 4(1):37–51, 1980. ISSN 1083-4419.

17

The gamma operator allows partial compensation.

18

Modeling objective	γ-model Network	Experiment & Results	Derived research	Summary Conclusion	
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γ- Operator

$$y = \underbrace{\left(\prod_{i=1}^m x_i^{\delta_i} \right)^{1-\gamma}}_{\text{"AND"-part}} \underbrace{\left(1 - \prod_{i=1}^m (1 - x_i)^{\delta_i} \right)^{\gamma}}_{\text{"OR"-part}}$$

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

- If $\gamma=0$ there is NO compensation (AND)
- If $\gamma=1$ there is FULL compensation (OR)
- If $\gamma=0.5$ there is Partial compensation (like mean)¹⁸

Can be AND or OR, depending on value of Gamma
 Delta_i is the weight factor relating to the input variable x_i
 (can be trained like weight in a NeuralNetwork)
 Gamma decides the degree of compensation (can be trained like bias in a NeuralNetwork)

> Use gamma-operator instead of weights, summation, bias and sigmoid/tansig in Neuron

19

Modeling objective	γ-model Network	Experiment & Results	Derived research	Summary Conclusion	
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Input selection & pre-processing

Selection based on mathematical analysis of visual cues: *information content vs. information needed for control*

Pre-processing:

- Normalization
- Addition of complement (= $1 - \text{norm.value}$)
- Detailed fuzzification is possible, but undesirable

19

A minimum set of input parameters was decided upon based on the mathematical analysis of several visual cues.

As we don't only want the input "IF the value of the visual cue is high ...", but also "IF the value of the visual cue is low ...", I added the complement for every input.

A more detailed fuzzification is possible, and a better fit of the human pilot data will be obtained. However, the number of parameters will increase and it will become more difficult to explain the resulting model to pilots/instructors in simple terms

20

Modeling objective	γ-model Network	Experiment & Results	Derived research	Summary Conclusion	
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Simulator Experiments

Figure 4.2: Photos of JAXA's MuPaI simulator

- JAXA ("MuPaI-α" FFS)
 - Dornier 228-200 TurboProp
- Fixed base simulator
 - Boeing 767-300
- ANA (All Nippon Airways) FFS
 - Boeing 767-300

Figure 4.3: Photos of the Boeing 767 and its simulator

20

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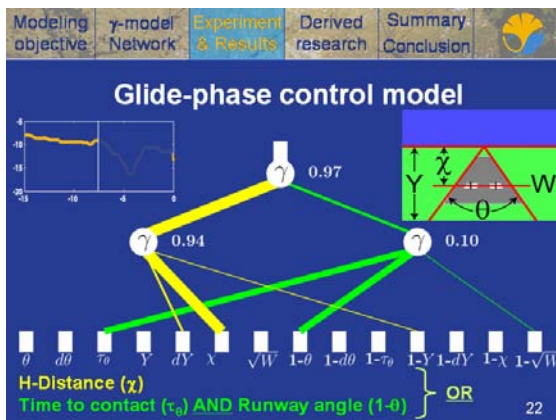
Most data I obtained in Level D Full Flight training Simulators (FFS). These are certified simulators and were operated by licensed pilots, so data should be very reliable and comparable to real data.

21



I collected data in a few real flights (using video cameras and offline image-processing we obtained visual cues and control inputs)

22



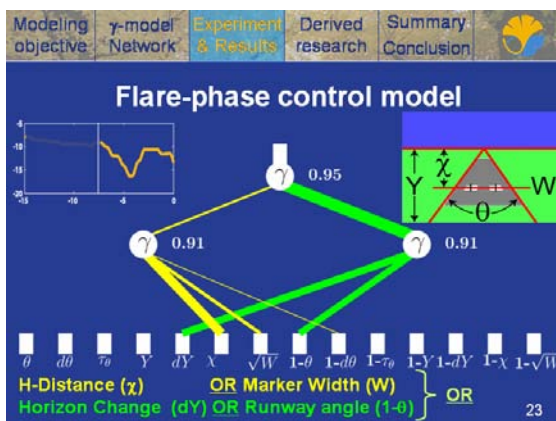
I show one example obtained from the MuPal (Do228-200 TurboProp) simulator.

For the glide phase the most important cue seems to be the H-Distance (distance between touchdown zone marker and horizon). The connection between the chi input and the output has the strongest weights (thickest lines). This is what we expected from literature.

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

Although this is a representative case for most data sets, several of the large aircraft (B767) landings showed Y and dY as main cues, rather than the H-Distance. It is thought that, due to the great stability of such large aircraft, simple “inner loop” pitch control suffices to keep the glide path. The experiment may have been insufficiently exciting all pilot modes. (Maybe more turbulence needed to get a more complete picture of visual cue needs)

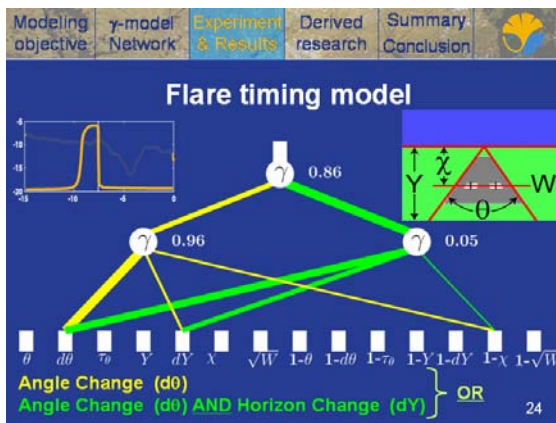
23



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 H-Distance 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.

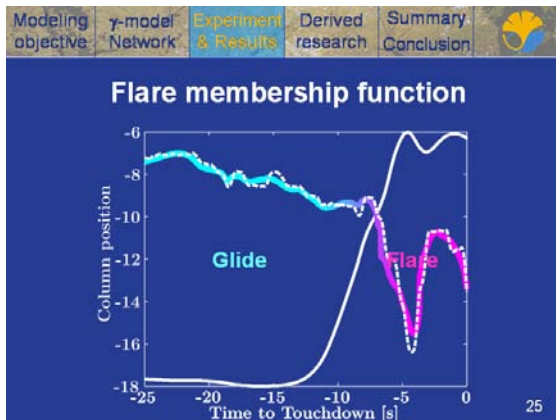
24



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 it has never been clearly mentioned in literature, as far as I know.

25

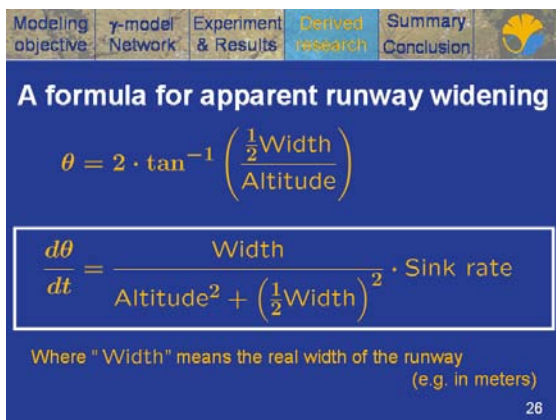


For verification of the results I discussed so far, I did the following test:

For modeling, I separated glide and flare phases manually. Now we know that dtheta and dY are high at the flare initiation. This means that the values of theta 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]

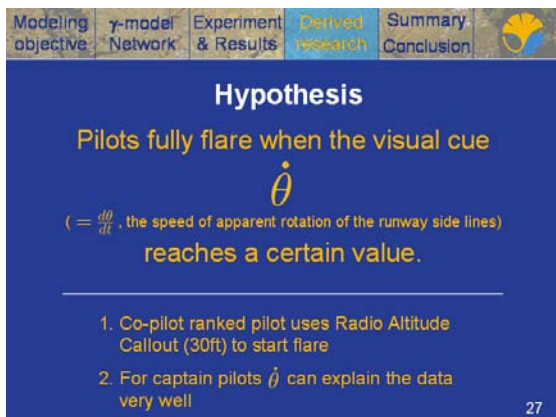
When we use this resulting membership function (solid) as a supervisory controller to mix the outputs of the glide model and flare model, we see it indeed makes a very sensible cut, and the model output (colored) closely resembles the original column data (dashed)

26



I further investigated the $d\theta/dt$ cue and derived these formulas. It is important to note that $d\theta/dt$ (the change of runway angle) includes both the altitude and the sink rate. These state variables were found to be important for the decision of flare timing. Therefore, $d\theta/dt$ cue is a suitable candidate cue.

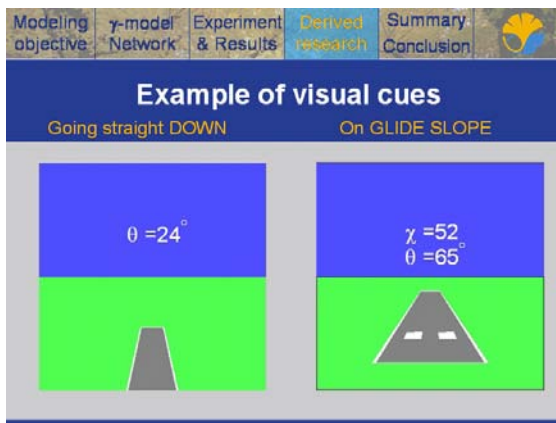
27



This led me to the hypothesis that “pilots use the $d\theta/dt$ cue to time the (full) flare initiation”

From dedicated simulator experiments, I found a co-pilot seemed to time his flare initiation based on the radio-altitude callout of 30ft (as suggested by the operations/training manuals), whereas the experienced captain pilots initiated the flare at higher altitude when their sink rate was higher (and generally quite a bit higher than 30ft). This behavior matched with the $d\theta/dt$ hypothesis

28



[videos] show how the scene changes when moving straight down (left) or on glide slope (right) at CONSTANT speed. When moving down, the shape changes (the apparent angle between the side lines, theta, gets bigger). Even at constant sinkrate, theta increases more than linear (as we saw in the formula before, $d\theta/dt$ depends on altitude as well as on sinkrate).

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.

29

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.

30

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For more information, please visit my website and download my PhD-Thesis or other papers.