5.12 Simulating Visual Attention Allocation of Pilots in an Advanced Cockpit Environment

Simulating Visual Attention Allocation of Pilots in an Advanced Cockpit Environment

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This paper describes the results of experiments conducted with human line pilots and a cognitive pilot model during interaction with a new 4D Flight Management System (FMS). The aim of these experiments was to gather human pilot behavior data in order to calibrate the behavior of the model. Human behavior is mainly triggered by visual perception. Thus, the main aspect was to setup a profile of human pilots' visual attention allocation in a cockpit environment containing the new FMS. We first performed statistical analyses of eye tracker data and then compared our results to common results of familiar analyses in standard cockpit environments. The comparison has shown a significant influence of the new system on the visual performance of human pilots. Further on, analyses of the pilot models' visual performance have been performed. A comparison to human pilots' visual performance revealed important improvement potentials.

1.0 INTRODUCTION

The European project HUMAN (EC's 7th Framework Programme) aims at developing virtual test pilots, in order to improve the human error analysis of future cockpit systems in early design phases, as a supplement of simulator tests with human pilots in later design phases. In HUMAN, a 4D Flight Management System (Advanced Flight Management System, AFMS) and its user interface (Airborne Human Machine Interface, AHMI), developed at the German Aerospace Center (DLR Braunschweig), have been selected as systems under investigation. The virtual test pilots are instances of a cognitive architecture named CASCaS (Cognitive Architecture for Safety Critical Task Simulation, see [12]). Cognitive architectures, such as ACT-R (see [1]), SOAR (see [10]), MIDAS (see [4]) and CASCaS implement cognitive plausible theories for human perception, memory operations and decision making. These theories are independent of specific human-machine interfaces. Thus, cognitive architectures are applicable not only in the aviation domain, but also in the automotive or maritime domain. Perception of system and environmental states – or of entities in the real world in general – is a key factor for situation awareness and for decision making [6]. The main channels for perception on human-machine interfaces are primarily eyes for visual perception and secondarily ears for auditory perception. A third upcoming channel is the skin for tactile interfaces, but this is – to our knowledge – currently not implemented in any of the cognitive architectures mentioned before. Due to the importance of visual perception for human-machine interaction, and for situation awareness and decision making, there is a need for an accurate simulation of visual performance in cognitive architectures.

Introduction of new user interfaces, e.g. into common cockpit setups, has influence on the visual attention allocation. Examples for this effect can be found in [7]. This could be explained by the following two points: On the one hand, new interfaces can trigger attention bottom-up, meaning that the interface presents information in a very dominant way which distracts visual attention from other interfaces. This is often referred to as selective attention, where eye movements and shifts of attention are triggered by the onset of a salient stimulus [16]. On the other hand, attention allocation can be affected top-down because the new interface provides new functionality or displays redundant information in a more accessible or usable way than other interfaces do. Top-down attention is caused primarily by underlying task models that comprise the allocation of visual attention.

Thus, a cognitive architecture that should simulate visual attention allocation humanlike requires both, valid cognitive theories for bottom-up attention and a valid task model embedding tasks on the new interface into the common task model for top-down attention.

In this paper we will present results of experiments with human line pilots and a pilot model interacting in a cockpit environment containing the AHMI. Although the datasets have also been used to validate the cognitive theories for visual attention allocation implemented in the model, the main focus of this paper is the validation of our task model for scanning activities in the new cockpit setup.

In the following section we describe top-down and bottom-up concepts for visual attention implemented in CASCaS (section 2). Then, the experiments conducted (section 3) and the results of these experiments are presented (section 4). The paper closes with a short discussion (section 5) and conclusions (section 6).

2.0 MODELING VISUAL ATTENTION

Visual attention allocation is a complex conglomerate of top-down (active) and bottom-up (reactive) processes triggering percept actions. Top-down and bottom-up attention compete against each other [3], e.g. a salient stimulus might distract pilots from tasks which they are focused on. This is often intended, e.g. in case of warnings. However, a salient stimulus might go undetected, because top-down attention causes the eyes to move to an area of interest where the stimulus is either out of the visual field or absorbed by a dynamic neighborhood. The cognitive architecture CASCaS implements both processes. In the following subsections we will describe how top-down and bottom-up processes have been implemented.

2.1 Top-Down Attention

The top-down attention is driven via three different levels of consciousness (see Fig.1), which are based on Anderson's three layers of consciousness named autonomous layer, associative layer and cognitive layer [2]. This is also in line with Rasmussen, who defined three levels of behavior, called skill-based, rule-based and knowledge-based [13]. While nearly zero consciousness is needed on the autonomous layer, almost full consciousness is needed on the cognitive layer, where decision making, planning and problem solving are located.

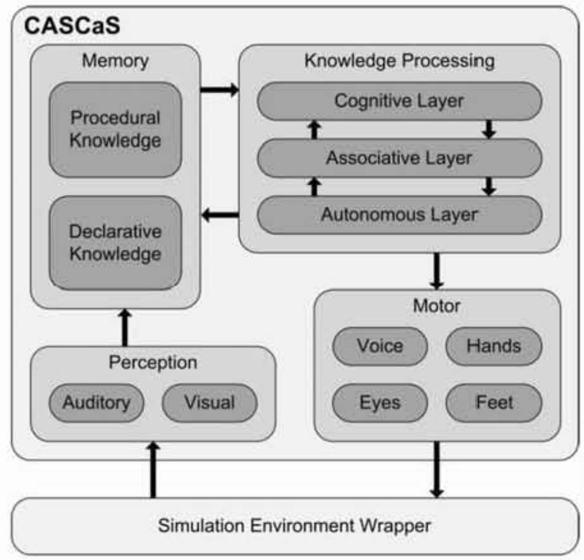

Fig. 1: The multi-layered architecture of CASCaS consists of components for perception, memory, knowledge processing and motor actions.

Top-down processes on the associative layer are the main driving factor for visual attention allocation of pilots, where they perform well-learned rules to achieve specific goals. These rules describe normative procedures – percept and motor actions that match correctly specific situations. With regard to visual attention of pilots we differentiate between two types of procedures: (1) scanning procedures and (2) interaction procedures. Scanning procedures only contain percept actions. Pilots regularly perform scanning of multiple aircraft and environment parameters in order to keep situation awareness for current and future aircraft states. These scanning activities are the main driving factor for visual attention in our pilot model. Interaction procedures contain percept and motor actions. They are used to interact with interfaces in the aircraft, such as the AHMI. Percept actions are needed in order to assess current situations and because we assume that pilots look at buttons before they press them.

In CASCaS, normative procedures are described by formal rules. The rule format is a Goal-State-Means (GSM) format (see Fig. 2). All rules consist of a left-hand side (LHS) and a right hand side (RHS). The left-hand side contains a goal in the Goal-Part and a State-Part specifying boolean conditions on the current state of the environment in the memory. Apart from the condition the State-Part contains memory-read operators to specify that, in order to evaluate a condition, the associated values v_i of interaction elements i_j have to be retrieved from memory. The right-hand side consists of a Means-Part containing motor and percept operators (writing values and reading values in the simulated environment), memory-store operators as well as a set of partially ordered sub-goals.

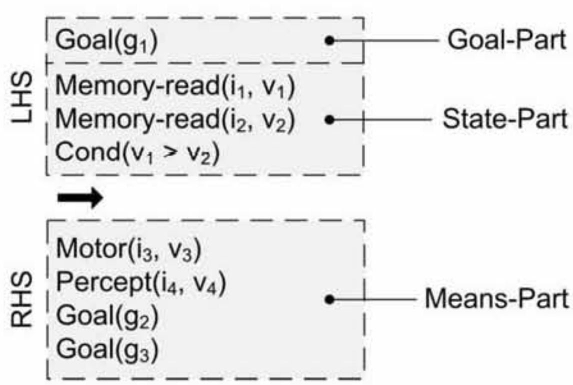

Fig. 2: Procedural knowledge is described is a specific rule format that consists a certain goal in a Goal-part, a State-part and a Means-part

During simulation the cognitive architecture selects rules based on their left-hand sides and executes the right-hand sides.

Rules are connected by a goal on the left-hand side and goals on the right-hand side. This allows us to break down complex procedures into a hierarchical ordered structure, similar to hierarchical task trees with a small difference: Our rule-based description of procedures permits transitions from lower levels to higher levels (see Fig. 3). Each procedure consists of *1…n* goals. Each goal is a unique entity that is allocated to *1…m* rules but each rule is allocated to exactly one goal.

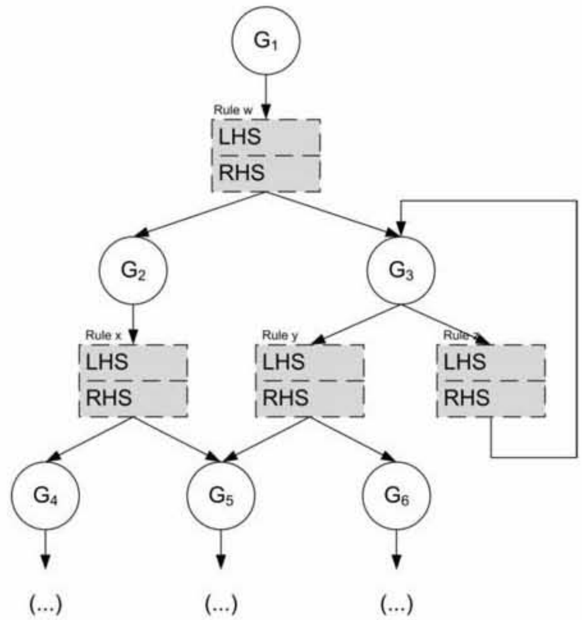

Fig. 3: Rules are connected by goals on the LHS and RHS

2.2 Bottom-Up Attention

Bottom-up processes are unconscious and triggered by the perceptual component of CASCaS. The main driving factor for bottom-up attention in CASCaS is a theory called selective attention. Selective attention is an effect where salient objects, e.g. flashing lights, moving objects, or high contrasts, cause an automatic shift of attention towards this object [16]. Attention shifts can also be triggered by acoustic and tactile stimuli, which are not investigated in this paper. In terms of visual stimuli, a salient stimulus means a discontinuity in space or time in the visual field. A discontinuity in space represents a difference in a static property, like color, brightness, form or orientation. This could be for example a green dot in a set of red dots. In contrast to this, a discontinuity in time – or dynamic discontinuity – denotes a dynamic change, like abrupt onset, flashing or moving of an object. This effect may be restrained by the top-down process or by the saliency of other objects nearby, which suppress, with their own high saliency, other salient objects.

Bottom-up attention can trigger specific procedures on the associative layer, e.g. in case of a flashing emergency light the attention of pilots should be shifted to the flashing light which is followed by execution of a procedure to handle the emergency.

3.0 EXPERIMENTS

In order to validate the visual performance of the model, experiments have been conducted with human subject pilots and with CASCaS in a functionally equivalent simulation environment. In the following sections, we will describe how the experiments with the human pilots have been carried out.

3.1 Target System AHMI

The main objective of our analysis is the interaction between the pilot flying (PF) and the AFMS. The AHMI is a graphical user interface supporting interaction between the AFMS and pilots. Both, the AFMS and the AHMI have been developed by the German Aerospace Center (DLR, Braunschweig, Germany). The AHMI supports graphical information about the current positions of the ego-aircraft and other aircrafts, weather conditions and flight routes. It provides a horizontal view (as shown in Fig. 4) and a vertical view. It supports onboard management of flight trajectories and negotiation of trajectory changes with Air Traffic Control (ATC) via Data Link to reduce voice-communication. The AHMI is a powerful tool for pilots, improving predictability of conflicts between aircraft or between planned routes and severe weather conditions.

Fig. 4: The AHMI, a graphical user interface supporting interaction between AFMS and pilots

3.2 Flight Simulator Setup

The experiments have been conducted in the GECO (Generic Experimental Cockpit) simulator, which has been built and is maintained by the DLR in Braunschweig. The layout of the simulator has been derived from the Airbus A350 XWB aircraft. It is equipped with freely programmable wide-screen LCD displays and modern input devices like side sticks and a Keyboard Cursor Control Unit (KCCU), as used in the A380. The flight dynamics are derived from a VFW 614 (ATTAS), as used by the DLR as a test aircraft. The outside view is generated via three video projectors on a spherical screen with a diameter of 6 meters, providing highly realistic outside view. The GECO is a fixed-based flight simulator equipped with a visual head tracker (AR-tracking), and an iView-X eye-tracker system from SMI. Eye-tracker data has been matched on specific regions representing areas of interest (AOI) where visual attention allocation should be analyzed. These AOIs were the following:

- Airborne Human Machine Interface (AHMI)
- Primary Flight Display (PFD)

- Horizontal Situation Indicator (HSI)
- Engine Display (ENG)
- Flight Command Unit (FCU)
- Gears and Auto Break (GAB)
- Outside view (Windows)

In addition, pilot voices and all flight parameters have been recorded.

3.3 Scenarios

In order to analyze pilot behavior, 8 scenarios have been defined, containing different AHMI-related tasks. The scenario that we refer to in this paper contained 3 events that pilots had to handle. These events triggered pilots to perform re-planning of their current flight plan according to requirements sent by ATC. A flight plan is a list of waypoints the aircraft has to fly over or fly by. The scenario was divided into three phases: cruise, approach and landing. Communication between pilots and ATC has been restricted to non-auditory communication via the AHMI which allowed uplinks or downlinks of flight plans.

3.4 Participants

The experiments have been conducted with 13 male and 2 female German line pilots recruited from German airlines. None of the pilots has been experienced in the usage of the AHMI, and only some have been in the GECO before. All subjects participated as the pilot flying (PF). The crew was completed by a scripted pilot, who acted as a pilot monitoring (PM). Scripted PMs were a male DLR test pilot or a female first officer from Lufthansa. In addition to the normal duties of the PM, the scripted pilot was responsible for the training and supported the debriefing and analysis by taking notes during the flight.

3.5 Procedure

The experiments were distributed over two days. The first day started with a general briefing on the project. Afterwards training on the AHMI and the GECO has been performed by the PM. After the pilots felt familiar with the tasks and the simulator, a talk-through was performed, in order to verify that the procedures where well-trained. After the talk-through was performed successfully, the subjects started to fly the first scenario. Typically, 2 scenarios were finished on the first day and 5 to 6 scenarios on the second day.

4.0 RESULTS

In this section we present results of analyses regarding top-down visual performance of human pilots and of our pilot model in a cockpit setup containing the AHMI. The analysis is based (1) on eye-tracker data, which have been recorded during the experiments with human pilots and (2) on log files for the pilot model. The output of both data sources has been pre-processed into a comparable format containing timestamps $t_{1...n}$ and AOIs $aoi_{1...m}$ describing where pilots have looked at a specific time. Each t_i in the datasets is associated with exactly one aoi_j. The experimental cockpit has been divided into 7 AOIs (see section 3.2) in order to analyze the gaze distribution. However, the results presented in this paper focus on 4 AOIs (AHMI, PFD, HSI, windows) which have been selected after a first review of the data for the following reasons: AHMI, PFD and HSI are the main displays for monitoring aircraft and environmental states in our scenarios during all flight phases. The windows are very important for perception of the outside world during the landing. We segmented the datasets according to 3 flight phases (cruise, approach, landing) and calculated the percent dwell times (PDT) for each phase, respectively. PDT is a format representing the dwell time spent on a specific AOI in relation to the sum of dwell time spent on all AOIs observed in (%). We analyzed the PDTs on two levels: First, we performed a separate comparison of the results of each phase for the human pilots and for the model. Second, a comparison of human data to model data has been performed.

4.1 Human Performance

The gaze distribution of pilots during flight can be seen as the main indicator of how important specific areas are for flying an aircraft – from a pilot's point of view. Huettig, Anders and Tautz [9] revealed the dominance of the PFD in modern glass cockpits with a value of around 40%. For the HSI a value of around 20% has been measured. This result is in line with results published by Mumaw, Sarter and Wickens (see [11] and [14]), who analyzed the monitoring behavior of pilots on an automated flight deck. They measured 35% on the PFD and 25% on the HSI. Futher on, eye movement analyses with a Boeing 747-400 desktop simulator have been conducted by Dietz et al. (see [5]).

In order to get an overview of our results, Table 1 depicts the average PDTs of our human subjects for each flight phase. Values do not sum up to 100 because dwells on other AOIs are still taken into account but are not displayed.

	Cruise	Approach	Landing
AHMI	60	42	21
PFD	15	28	40
HSI	7	11	12
Windows	6	7	17

Table 1: Aggregated PDTs of human pilots during flight phases cruise, approach and landing

In contrast to results mentioned above, our results reveal a dominance of the new introduced AHMI with a value of 60% during cruise phase. The PFD, with a value of 15%, is far behind the AHMI. This emphasizes the role of the AHMI in our scenarios. HSI, with a value of 7%, is behind the PFD, which is in line with results reported in literature. During cruise outside view is not important, thus, with a value of 6%, windows are behind the HSI. From cruise to approach PDT on PFD increases by 13%, while PDT on AHMI decreases by 18%. HSI is also increasing by 4% and windows by 1%. From approach to landing PDT on PFD is increasing by 12% and PDT on AHMI is decreasing by 21%. PDT on HSI is increasing by 1% and PDT on windows is increasing by 10%. Thus, from approach to landing the rank orders of AHMI and PFD change as well as the orders of HSI and windows. We assume that changes in gaze distribution between different flight phases are caused by different task models for each flight phase. E.g. the high values on windows during landing phase are caused by the upcoming landing task which triggers the pilot to monitor the runway. Low values on the AHMI during landing phase are caused by degradation of the navigation task. These changes are caused by top-down attention as described in section 2.1.

4.2 Model Performance

Results of model performance show, with a value of 65%, a strong dominance of the AHMI during cruise phase. With a value of 31%, the PFD is behind the AHMI. From cruise to approach there is only a small change to 66% on the AHMI. PDT on PFD does not change. From approach to landing rank orders of AHMI and PFD change. PDT on AHMI decreases from 66% to 35% and PDT on PFD increases from 31% to 53%. HSI and windows are at a very low level between 0% and 2% during all phases. All results are presented in Table 2.

	Cruise	Approach	Landing
AHMI	65	66	35
PFD	31	31	53
HSI	0	2	2
Windows	1	1	1

Table 2: Aggregated PDTs of pilot model during flight phases cruise, approach and landing

4.3 Model Validation

Human performance data has been used to validate the visual performance of the pilot model based on two dimensions, trend and local fitness, that are often used in the domain of cognitive model validation.

4.3.1 Measure of Trend

A trend describes how a dependent variable v_d develops in relation to an independent variable v_i. We have measured the variable gaze distribution (= v_d) in relation to the flight phases (= v_i) for the human pilots and for the pilot model. An aspect of model validity is trend consistency, meaning that the relation between v_d and v_i is the same for the model and for the real world aspect observed. In the area of cognitive model validation, the use of Pearson's correlation coefficient (r and r^2) is a common measure of trend (see e.g. [7] and [15]). Having a look at the performance of the pilot model applying our scanning procedure, it can be seen that it fits the human visual performance rather well with $r^2 = 0.85$.

Figure 5 visualizes trends based on PDTs measured for the human pilots and for the pilot model during the flight phases cruise, approach and landing.

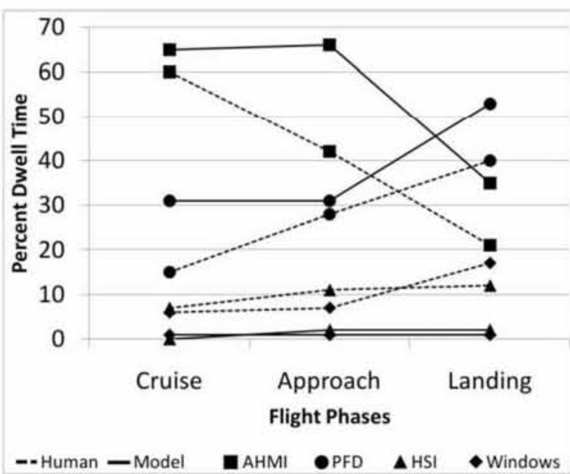

Fig. 5: Comparison of gaze distribution for human pilots and pilot model across flight phases

AHMI and PFD are the most dominant displays during all phases for human pilots and for the pilot model. AHMI and PFD change their ranks order from approach to landing phase. The human data trends for AHMI and PFD between cruise phase (AHMI = 65%; PFD = 31%) and approach phase (AHMI = 66%; PFD = 31%) have not been captured for the model. Indeed, the trend for AHMI between these phases is slightly contrary to the human findings. The human data trend on HSI has been well captured for the model, where PDT is increasing from cruise (= 0%) to approach (= 2%) and then holding the level from approach to landing (= 2%). The model's PDTs for the windows are linear for all flight phases (= 1%). We had problems modeling this AOI, because dynamic AOIs, such as a runway "moving" on the windows, currently cannot be modeled within the architecture. Thus, we are not able to provide the model with information that is gathered by human pilots when they are looking out of the windows. Nevertheless, during our experiments we implemented some kind of "blind scanning" on the windows in order to simulate transitions between windows and displays. The intention was to model the effect of not looking at displays (for whatever reason) which has been identified as a cause for long reaction times because visual signals such as flashing buttons are not in the visual field (see section 2.2). This may also impact pilots' situation awareness.

4.3.2 Measure of Location

We analyzed the local fitness of gaze distribution by comparing the Root Mean Squared Successive Differences (RMSSD) values of human pilots and the pilot model as presented in [14]. Local fitness measures of model to human data are a bit problematic as trying to optimize local parameters bears the danger of overfitting the model. Instead of fitting the model to a static parameter value, it is more reasonable to fit the model into a range of parameter values. RMSSD can be used to gain insight into the differences of performance between an individual subject s_i and a group g_j of individual subjects $s_{1...n}$. We calculated RMSSD for each of the human subjects, pulling them one at a time, without replacement, from the group. In our case the group contained 10 subject datasets and we tested the fit of s_1 to $s_{2...10}$, then data from s_2 to s_1, $s_{3...10}$ and so on. The results of these measures were 10 values, one for each pilot, describing the deviation from the performance of the group. This approach has been extensively described in [8]. We also calculated RMSSD for our pilot model by comparing the model dataset to the group of all human subjects $s_{1...10}$. Next, we will focus on results regarding the cruise phase as this is the most important phase for pilot interaction with the AHMI. Results are depicted in Fig. 6. RMSSD values for human subjects range from 5.52 for subject PF_03 to 24.11 for subject PF_09. The RMSSD for the pilot model is 19.21 which is within the range of human subject values. However, a comparison of this value to the median of human pilots' RMSSDs (= 7.63) shows that the model result is closer to the maximum than to median.

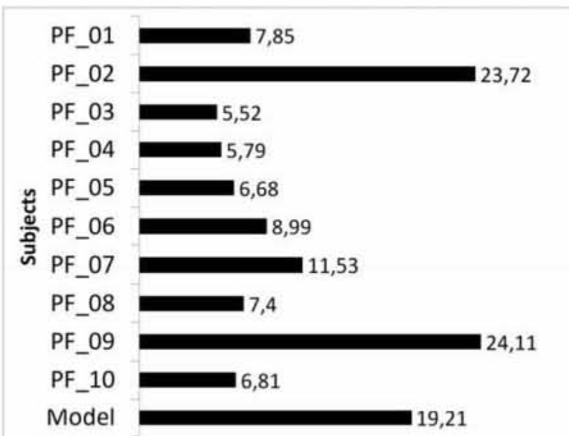

Fig. 6: Comparison of RMSSD values for PDTs of human pilots' and pilot model's gaze distribution in cruise phase

Except for subjects PF_02 and PF_09 all pilots are below a value of 12.0 which shows that these results are outliers in the sample. Analysis of outlier datasets showed that the deviations are caused by differences in PDTs on the AHMI. We have measured 60% mean PDT and 61% median PDT on the AHMI which is a hint on a well-balanced distribution. For PF_02 we have measured 80% PDT (= max) and for PF_09 we have measured 39% PDT (= min). PDTs of PF_02 on other AOIs were much lower, those of PF_09 much higher respectively. An explanation could be that PF_02 used redundant information shown on the AHMI (such as speed, altitude) for monitoring. Thus, he has implemented the AHMI in his scanning procedure (top-down attention). On the other hand, PF_09 used the AHMI only if he had to react to ATC uplinks (bottom-up attention) instead of including the AHMI into his scanning procedure.

5.0 DISCUSSION

Analysis of visual attention is a useful means for assessment of situation awareness and derivation of task models for scanning activities in cockpit environments. We have modeled scanning procedures for an advanced cockpit environment and performed experiments with a pilot model applying this procedure and with human subject pilots. We used the visual performance data recorded for the human pilots and for the pilot model to validate the visual performance of the model. While Pearson's r and r^2 are useful trend measures, RMSSD can be used to measure the local match between model and human data. Good results for Pearson's r and r^2 are not sufficient to validate a model. A valid model must also perform within the natural range measured for the variable under observation of the human subjects. Comparing our result for the trend measure between human pilots' and model gaze distribution with the results of local fitness, we derive the following: As the trend measure between model and human performance revealed good fitness, we assume that we have a rather good assumption of how important specific AOIs are for the pilots relatively to the flight phases. As the gaze distribution is a good indicator for the correctness of the scanning tasks in the different flight phases, we also assume that we have a correct understanding of the importance of specific scanning tasks performed in these flight phases. However, RMSSD revealed that the performance of the model is at the upper bound of human subjects' performance. This can be improved by decreasing gaze on AHMI and PFD, and increasing gaze at least for the HSI, which has not been modeled sufficiently. Gaze on the windows has not been modeled adequately. It has to be discussed if it is reasonable to put attention on an area, whose functionality cannot be simulated, only to provoke effects related to bottom-up attention. Alternatively, only flight in cruise phase could be modeled, which has shown to be the most relevant flight phase for AHMI interaction.

6.0 CONCLUSIONS

In this paper we have presented results concerning the visual attention allocation of human pilots and of a pilot model in an advanced cockpit environment. We have been able to show that the AHMI, a new interface for aircraft navigation, has a strong influence on the gaze distribution of pilots due to task models underlying the flight phases. Tasks (especially scanning activities) have been modeled in a rule based language. These rules have been applied by our pilot model as procedural knowledge during the flight phases. Analyses of human pilot performance and model performance in the dimensions of trend and local fitness revealed that there is still some potential left for improving the scanning behavior of the model. An open question is if it is useful to model "blind scanning" on AOIs whose functionality cannot be simulated in order to provoke effects related to bottom-up attention.

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8.0 ACKNOWLEDGEMENTS

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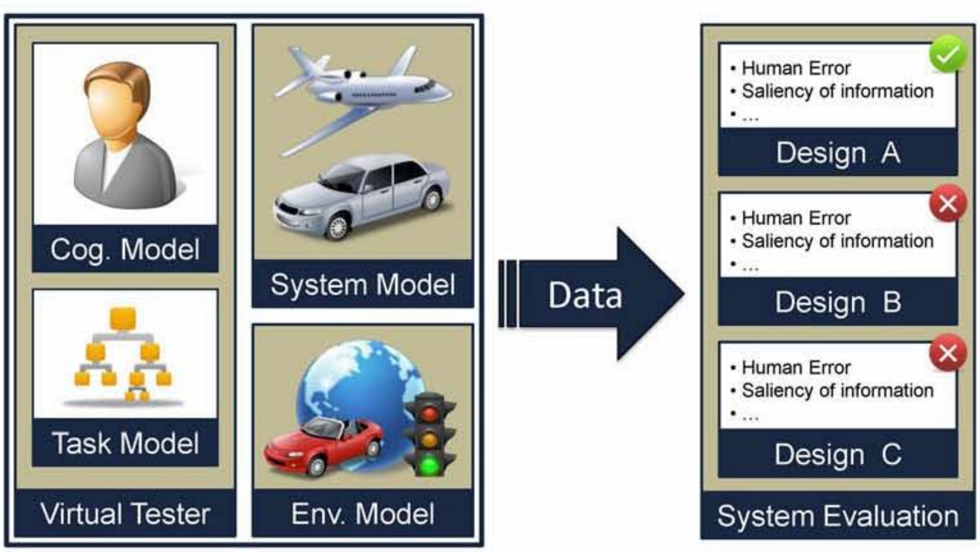
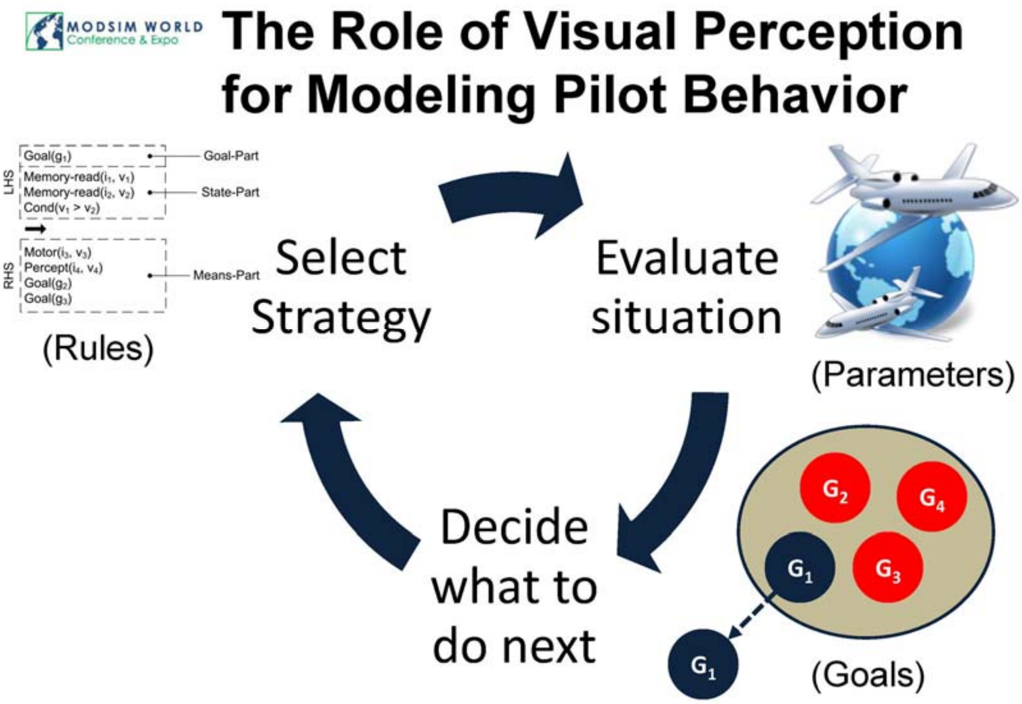
Motivation



Support evaluation of system designs in early phases of system development process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The Role of Visual Perception for Modeling Pilot Behavior
LHS
Goal(g1)
Goal-Part
Memory-read(i1, v1)
Memory-read(i2, v2)
State-Part
Cond(v1 > v2)
RHS
Motor(i3, v3)
Percept(i4, v4)
Means-Part
Goal(g2)
Goal(g3)
(Rules)
Select Strategy
Evaluate situation
(Parameters)
Decide what to do next
G2
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G3
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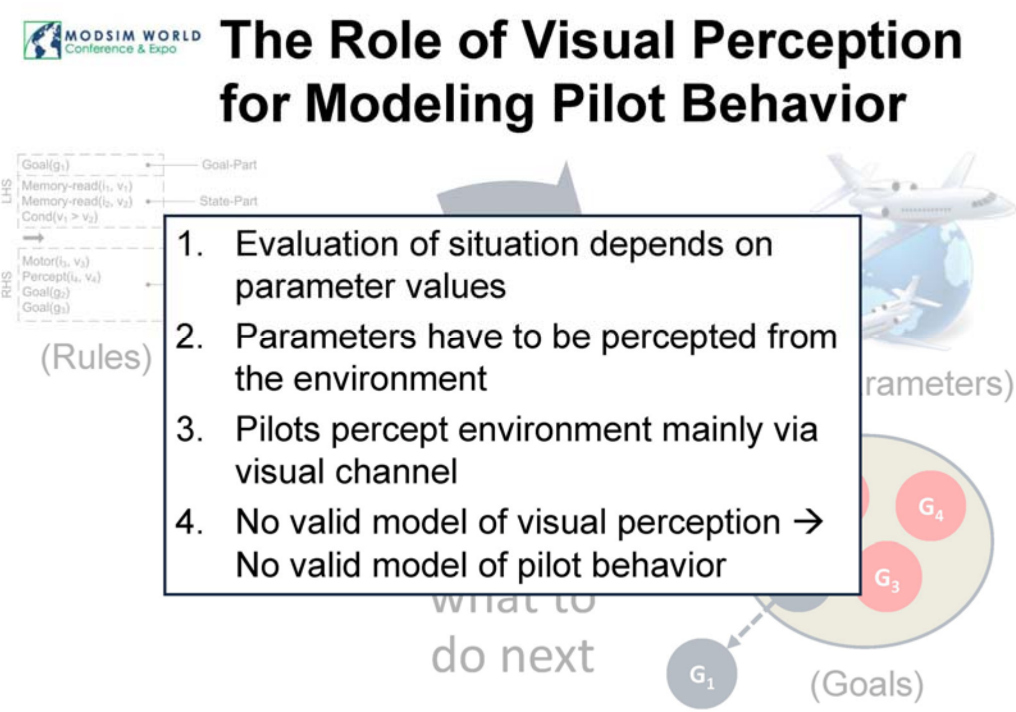
(Goals)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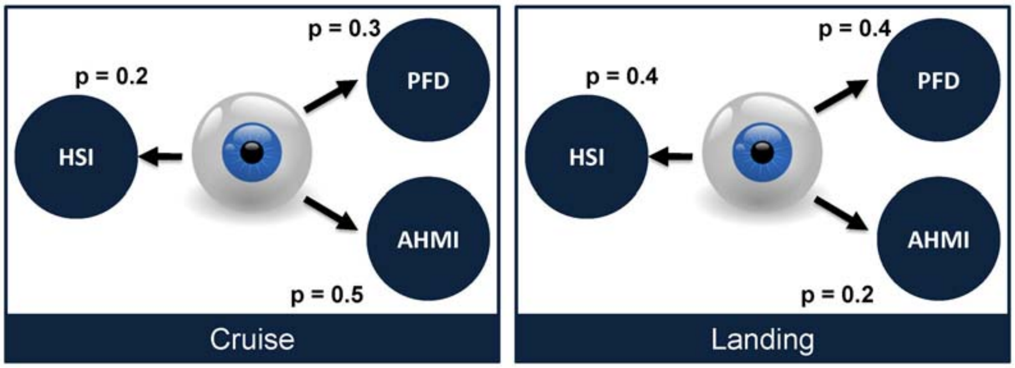
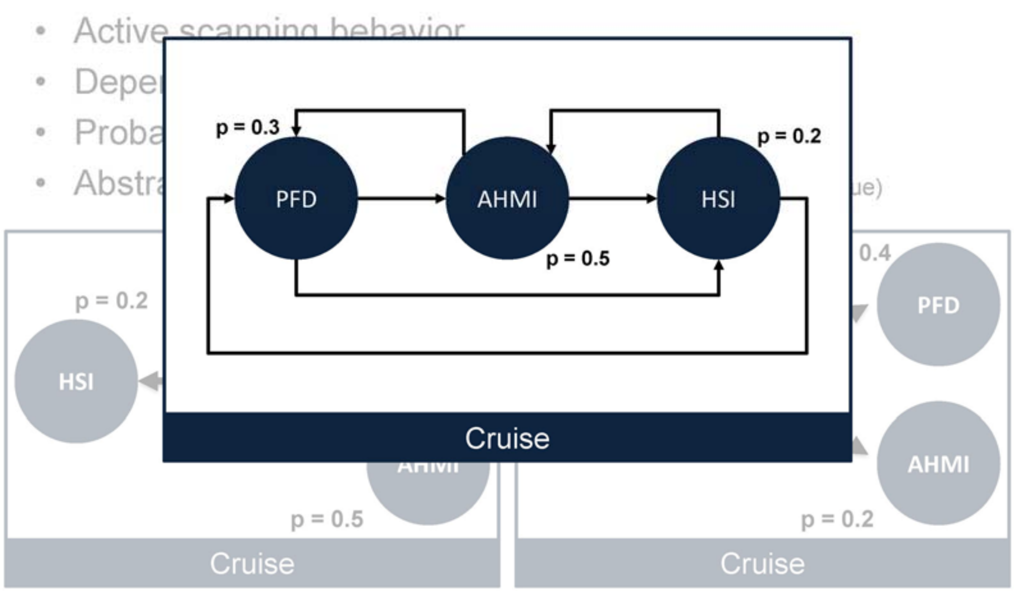
The Role of Visual Perception for Modeling Pilot Behavior
1. Evaluation of situation depends on parameter values
2. Parameters have to be percepted from the environment
3. Pilots percept environment mainly via visual channel
4. No valid model of visual perception → No valid model of pilot behavior

Visual Attention: Top-Down

- Active scanning behavior
- Depends on context of situation
- Abstraction of SEEV Model (Saliency, Expectancy, Effort, Value)
- Probability value for each AOI

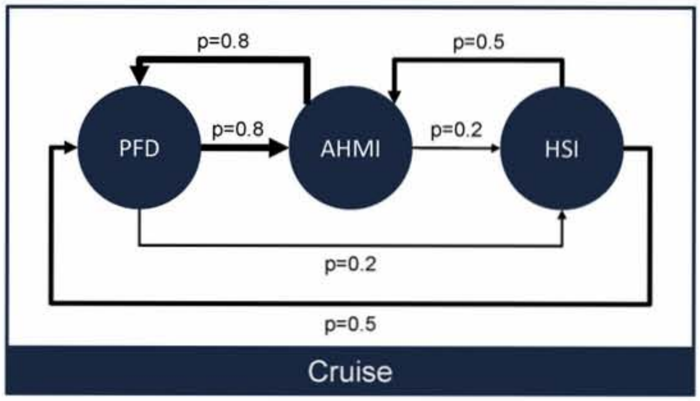


Visual Attention: Top-Down



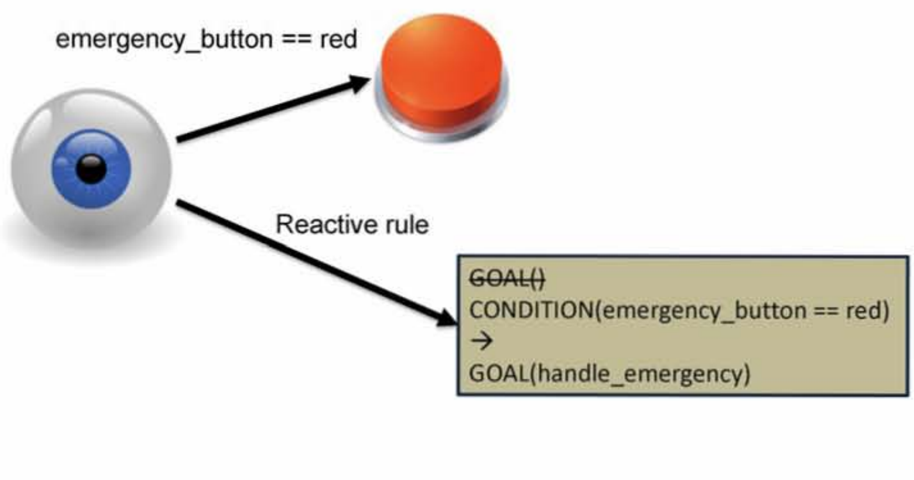
Improved Top-Down Attention

- Pilots tend to optimize scanning behavior
- Probabilities on transitions between AOIs
- Different probability values for each transition



Visual Attention: Bottom-Up

- Reactive scanning behavior
- Depends on saliency of objects in visual field
- SEEV Model → Saliency

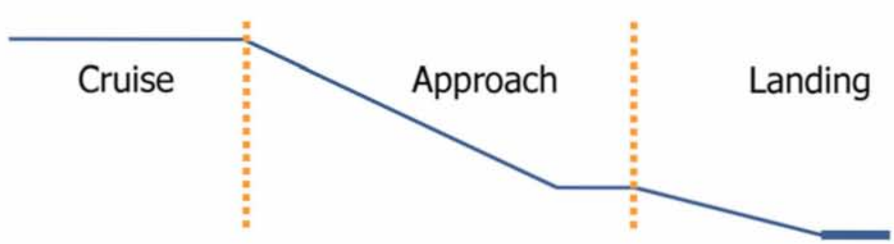


Visual Attention Model

- Consists of
  - Top-down attention (active)
  - Bottom-up attention (reactive)
- Visual attention is mainly influenced by top-down attention
  - Considers context of different situations
  - Supports modeling of human optimization strategies

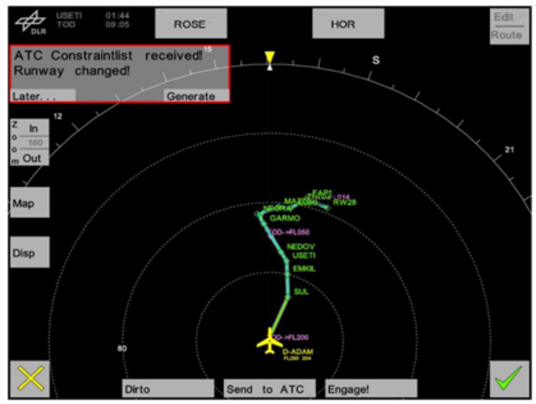
Experimental Setup

- Scenario duration: ~35 minutes
- 15 Airline pilots
  - 13 male, 2 female
  - Average Age: 34.0 (SD 5.9)
- Events triggering re-planning on AHMI
- Three flight phases:

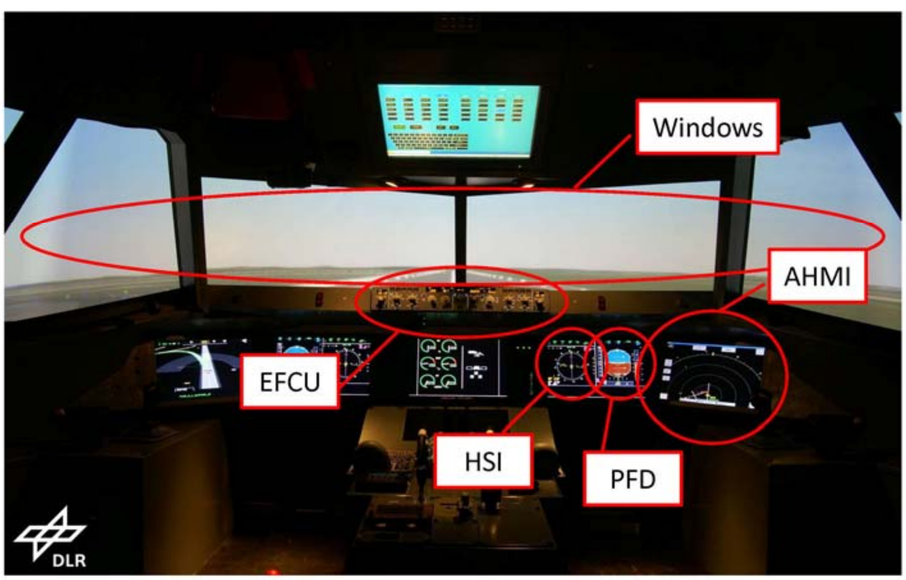


Target System: AHMI

- **A**irborne **H**uman **M**achine **I**nterface
- Data link communication between Crew and ATC
- Negotiation of 4D flight plans and trajectories
- View on ego-aircraft
  - Horizontal
  - Vertical

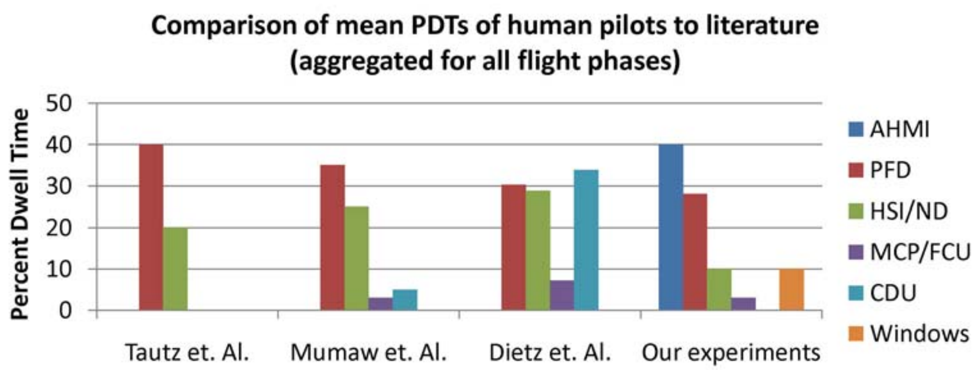


Simulator Layout and AOIs

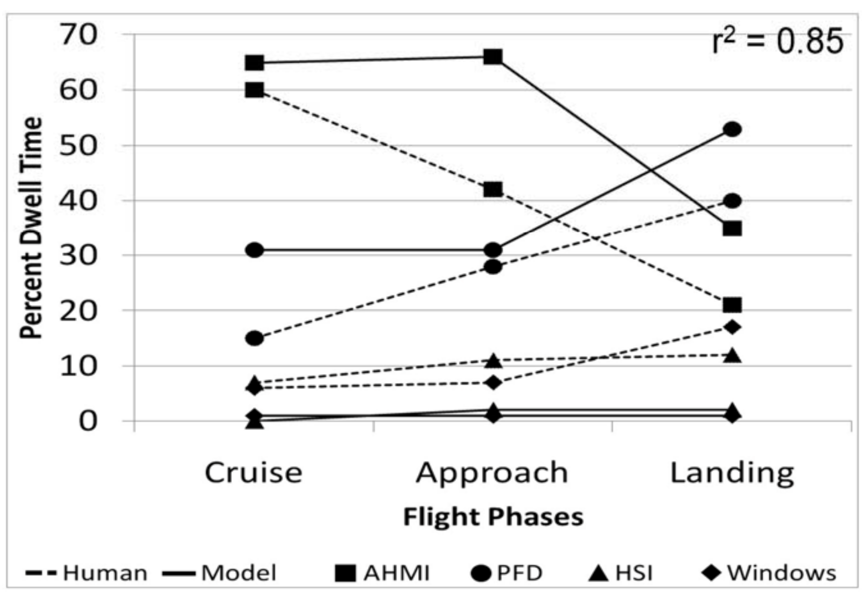


Results

- Focus of pilots' attention is mainly on AHMI
- AHMI has no influence on rank order of standard displays

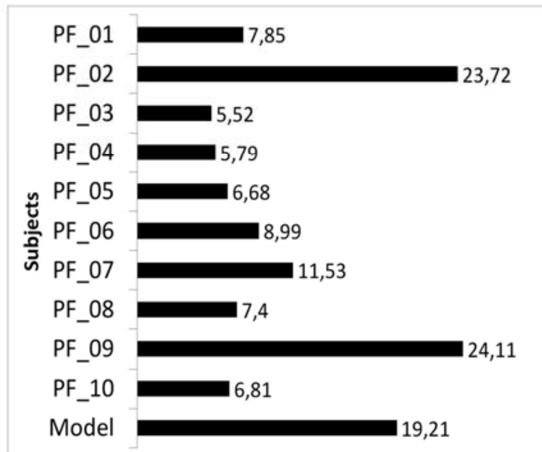


Measure of Trend



Measure of Location: RMSSD*

1. Calculate individual difference of each human pilot to the group
2. Calculate difference of virtual pilot to the group
3. See if model is in range of human performance



*in cruise phase

Questions/Comments

Thank you for listening!

Any questions?