Simulating the Impact of Mental Models on Human Automation Interaction in Aviation

Sebastien Mamessier and Karen Feigh

Georgia Institute of Technology, Atlanta GA, USA

Abstract. This work proposes a computational approach supporting the simulation of human automation interaction in aviation. The development of an advanced human agent model that accounts for workload limitations, imperfect mental models and consequences on the operator's situation awareness provides new insight for future certification procedures regarding human interaction with complex automated systems.

1 Introduction

Commercial pilots are faced with growing complexity of automated flight systems. Although most of these new systems are known to be robust to small disturbances and failures, humans still play a crucial role for advanced decision making in off-nominal situations and accidents still occur because of poor human-automation interaction. Usual mechanisms to investigate the influence of new automation on human automation interactions includes extensive use of simulation and human-in-the-loop (HITL) experimentation. But simulators and HITL experiments are expensive, time-consuming and not comprehensive as far as diversity of scenarios is concerned. Therefore we need to improve our simulation capabilities by developing realistic computational human agent models taking into account human limitations.

Maintaining a good understanding of the situation including the behavior of the automated flight systems is critical for the flight crews to make appropriate decisions in both nominal and off-nominal cases. Therefore a realistic human agent model should account for the situation awareness of the flight crew. The concept of situation awareness [5] is a good base of projection of the pilot's immediate understanding of the situation but it is not sufficient to explain its evolution. Certain operators are able to maintain a good situation awareness despite of off-nominal external inputs or degraded monitoring capabilities by developing an accurate mental model of the system. However, when the operator has a deficient mental model of the automation, his situations awareness tends to decline and result in loss of control situations.

A key contributor in the difficulty pilots have in maintaining both adequate situation awareness and an accurate mental model is the large number of automation modes, transition rules and their relative opacity to the pilot. This is particularly noticeable for transition scenarios that are rarely faced by the crew. The specifics of these transition scenarios tend to be forgotten but may be

V.G. Duffy (Ed.): DHM/HCII 2013, Part I, LNCS 8025, pp. 61–69, 2013.

critical to fully understand off-nominal situations. As the primary mechanism to import the knowledge of the systems dynamics, rules and procedures to the flight crew, additional training has been the typical response to poor human automation interaction. Enhanced training improves the comprehensiveness of the operator's mental model of the system, but has its limits, especially in light of tight training budgets. And as the mental efforts needed to maintain a good situation awareness are correlated to the number of dynamics/rules to remember and consider, i.e to the complexity of the automated systems, some have begun to question the wisdom of including even more specialized automation into the flight deck, and how to adequately certify future flight deck automation.

This works proposes a computational method to implement mental models and simplified agent training as well as workload limitations into a work simulation tool, taking into consideration implicit knowledge alteration of discrete mode based dynamics and simulate the consequences of inaccurate mental models on Situation Awareness. Such an approach could allow future certification procedures to account for faulty mental models which are a serious cause of human automation interaction breakdowns in aviation.

2 Work Models and Mental Models: Background

2.1 Modeling Work Domains

Vicente [12] defines a work domain as the *The system being controlled, independently of any particular worker, event, task, goal, or interface.* A key part of this effort is to find an adequate formalism for *work domains* before integrating *mental models*. Rasmussen and later Vicente developed an extensive theory of cognitive system engineering that describes the functional structure of these *work domains* [12]. Pritchett et al. in turn, proposed a method to parse such functional descriptions into computational work models [11] while preserving the concept of situated cognition using advanced human agent models. Simulating *work models* has been done using the work simulation framework WMC (Work Model that Computes) used in [11].

2.2 Defining Mental Models

An extensive literature on mental models exists comprised of contributions from multiple scientific communities. System dynamics scientists were the first to introduce the concept of *mental model* with Forrester [7] about industrial dynamics applying this concept to corporate organizations and processes. Psychology and cognitive science also put some effort at defining *mental models* among other cognitive structures whereas Human Computer Interaction was the first field using the concept of *mental models* to address issues in human-in-the-loop systems. Finally, Doyle and Ford drew an extensive survey of the different interpretations of *mental models* of socio-technical systems in these fields to state a precise definition [3], framing the concept of mental models as enduring, but limited internal representations of the system, its environment and procedures.

2.3 Implicit Learning

Forrester was already addressing the changing nature of mental models : “within one individual, a mental model changes with time and even during the flow of a single conversation” in 1971 [8]. Javaux explained how implicit learning alters the knowledge of finite state systems using the concept of Hebbian Learning to update the mental representation of rules as the agent experiences transition scenarios [9]. Hebbian learning has been extensively described in the neuroscience literature [1,2] as a basic model of long-term synaptic plasticity.

3 Creating a Computational Work Model

Based on the approach described by Pritchett et al. [11] and using Work Models that Computes (WMC) as a computational modeling framework, this work introduces a systematic way of breaking down work models into semi-specialized actions to enable more realistic interactions between a human agent and its environment.

3.1 Work Model that Computes (WMC)

WMC (Work Model that Computes) is a simulation framework developed to model realistic work environments, taking into consideration continuous dynamics, discrete actions, human agent models and computing human-related metrics such as Workload and Performance [11.] It has been used to simulate aircraft and Air Traffic Control to test new Continuous Descent Approach patterns at Los Angeles Airport in Kim’s work about human-automation function allocation 10.

3.2 Decomposition of Work Model Actions

The fundamental premise behind the WMC simulation modeling framework is that the knowledge of the entire work domain can be captured independently of the agents who are asked to perform the work. However, we want to allow a specific instance of a human agent model to gain knowledge about the system and this knowledge to change over time for example through training. In order to guarantee a generic interfacing between work model and agent models while allowing experienced agents, we need to define a certain number of conceptually different action types.

Continuous Dynamics Actions. WMC is a continuous-time simulation engine. Its therefore capable of integrating numerically differential equations allowing to simulate complex non-linear system dynamics. These actions are executed by a non-human agent and generally include controllers and can implement a variety of numerical integration methods such as Runge Kutta.

Discrete Dynamics Actions. Complex automated systems such as Flight Management Systems comprise discrete modes of operations. Autopilot flight modes is a good example of complex mode transitions potentially confusing the pilot [9]. Since these modes change the control law and the aircraft behavior they have to be implemented by the modeler and their transition rules are assimilated to discrete dynamics actions.

Tasks. Although Vicente excludes task from the definition of work domains, a work model aims to implement the work to be performed, independently of the agent responsible for performing it. However, some attributes of the task such as the its duration and the consequent workload are directly dependent on the agent and are defined while linking a specific agent to the task during the function allocation step of the simulation's initialization. A task are usually atomic actions such as "Engage Autopilot" that can either be performed by the pilot or automation.

Monitoring Actions. Monitoring actions are meant to be executed by human agents. They implement the perception phase and therefore the first level of Situation Awareness. The frequency can either be procedurally fixed to a certain value or set dynamically.

Decision Actions. Decision Actions implement differential behavior. They can be assigned to either automation or human agents. The implementation itself only contains the procedural decision-making rules whereas mechanisms supporting information seeking, consideration of risks come under the implementation of the agents and not the work model. Decision Actions implement the response to change in the environments and therefore can schedule tasks or change the function allocation between agents.

4 Advanced Human Agent

Agents are the other end of a situated work simulation tool such as WMC. They do not have a priori knowledge of the work but are assigned actions from the work model and perform them according to their internal limitations and priorities. An automation agent will execute actions it has been assigned immediately whereas human agents can only undertake a limited number of actions simultaneously thus requiring any additional actions to be delayed depending of their current workload. This works uses the concept of agents introduced by Pritchett et al. [11] and enhances the human performance agent model used by Feigh et al. [6] by adding new constructs believed to account for Situation Awareness and Mental Models as shown in Figure 1. The previous labeling of actions now allows advanced human agents to execute actions differently according to their type. This way, monitoring actions will have an impact on the Situation Awareness and decision actions will depend on it.

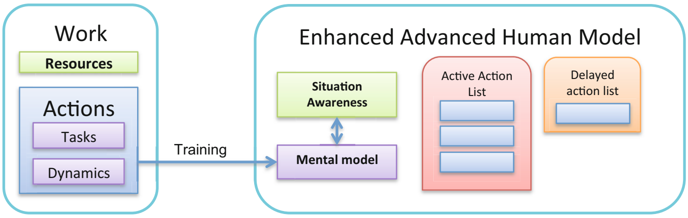

Fig. 1. The implementation of the work model and human model are independent. The mental model get initialized through a generic process that imports knowledge from the work model to an instance of the human model.

4.1 Simulating Situation Awareness (SA)

Situation Awareness is a crucial aspect in the analysis of loss of control situations [5,4]. The temporary loss of important sensors, false alarms or non-consistent information can sometimes be compensated for by a good understanding of the current state of the system and even more through anticipation of likely next actions. Whether the operator has a good or poor situation awareness depends on several factors such as his mental model of the system he is using and the degree of degradation of the situation. Whatever reason is causing an alteration of situation awareness, we need to project this concept onto computational constructs that can be used in simulation.

Perception and Workload (SA Level 1). Situation awareness Level 1 mostly describes the comprehensiveness and accuracy of the operator's perception of available cues about the state of the system [5,4]. Did the driver see the car in his right side-mirror? Did the pilot hear the aural stall warning? and so on. Certain monitoring schemes such as the T-screening for pilots are part of the training and are performed on a recurrent basis depending of the available mental workload. If the pilot is talking on the radio or to his copilot, he might skip one of these monitoring actions and his SA begins to degrade. By having the computational human agent model stacking monitoring actions as well as communication and actual physical actions in a active mental action list with limited capacity, we can simulate a degradation of the monitoring process and situation awareness L1. If the active action list gets saturated, actions get delayed or interrupted and can be even forgotten.

Understanding and Decision-making (SA Level 2) : Bayesian Approach. Situation Awareness Level 2 describes the understanding of the perceived cues, the identification of variables of interest (close to dangerous boundaries for instance), and includes some of the decision making process necessary for the human to consistently operate the system in response to environmental inputs [5,4]. Expert human agents are believed to maintain a belief of the state of the system as well as a degree of confidence that can be high for variables directly monitored on trustful instruments and very low in case of inconsistent or out-of-date information. A novice operator is more likely to apply procedures and rules all the time whereas a more experienced agent will selectively consider risks and other contextual information. The expert will reason using bayesian decision-making. Such an approach doesn't only use the last monitored value of a variable as a basis for decisions but also the degree of belief that one has about it. To model such behaviors, we can introduce the *mental state* of the system as a set of probability distributions. Each of them represents an actual variable of the system and is centered on the current belief of its value and stretched in or out as confidence decreases or increases. By assuming normally distributed belief variables, the mean of the mental variable is the actual belief of the corresponding system's variable and the standard deviation represents the degree of confidence. Using a gaussian representation has many advantages. First, its easy to manipulate and really memory-efficient. Indeed, we only need to store the mean and the standard deviation. Furthermore, this work will address mental models and model-based observers such as Kalman filter and how they change the operator's state representation between or in the absence of available monitoring actions. Kalman filters assumes a gaussian representation of variables. Also these probability distribution implement a bayesian rather than frequentist interpretation of probabilities. This means that the pilot does not sample from the distribution by accessing his working memory but simply reads the expected value, i.e the mean. The standard deviation does not represent his inability to remember or access to the actual value but his confidence in the value of this variable.

Non-gaussian Distribution and Cognitive Dissonance. In some situations, human operators can have a multi-modal belief of certain variables that can lead to inconsistent actions or so-called cognitive dissonances. In the AF-447 accident report by the BEA, the experts conclude several times that pilot flying hesitated between identifying an overspeed or stalling situation leading to non-consistent action sequences and eventually to the crash of the aircraft. In such a case, the mental representation of the speed of the aircraft cannot be fully captured by a gaussian variable. Allowing multi-modal probability distribution, like a sum of gaussian distributions can provide this capability.

4.2 Mental Models

A mental model is comprised of mental (perceived) dynamics of the system that allows the operator to update its mental belief between monitoring actions using the knowledge of covariance between variables and exploit partial observations to maintain a good situation awareness. Moreover, a reliable mental model allows anticipation (SA L3) and a smarter use of the limited available workload. An overview of how mental models fit into the simulation scheme and interact with Situation Awareness is depicted in Figure 3.

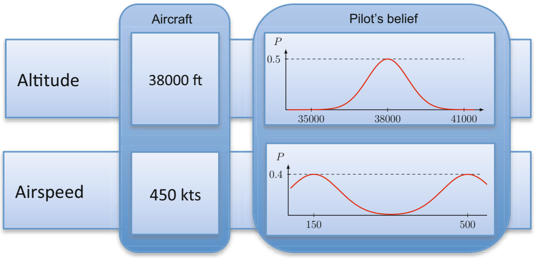

Fig. 2. The operator's belief is generally centered on the actual value of the state it represents. When sensors are not available anymore, the belief can diverge from the actual value and even be multi-modal. In the AF447 accident case, the pilot did not know whether he was in an overspeed or stall situation.

The following introduces two new types of actions that approximate the dynamics actions implemented by the modeler and whose behavior can change in response to implicit learning.

Continuous Mental Dynamics Actions. By contributing to maintaining an accurate mental representation of the state of the world, internal dynamics are an important part of mental models. They reflect and approximate the actual dynamics of the system and inform on operator's expectation. The accuracy of such mental dynamics depend on the training / initial knowledge of these dynamics, the experience/observation that the operator has of the actual dynamics and the amount of cognitive attentional resources available at time t in the WMC Simulation framework. Since agent models don't have a priori knowledge of the work model, the training of the dynamics must be added at the linkage step. The modeler decides which dynamics he would like the human agent to know. Dynamics hidden to the human agent will not update the human operator's belief of the related resources and lead to a lower situation awareness. On the other side, training the operator on too many dynamics might lead to overwhelming his limited mental capacity.

Discrete Mental Dynamics Actions and Implicit Learning. Javaux's work illustrates [9] how the pilot's knowledge of discrete rules, automation mode transition can impact situation awareness and therefore have to be part of the mental model. An inaccurate knowledge of automatic mode reversions of the Autopilot can lead to a problematic mode confusion. Transitions between mode invoke complex engagement conditions and some of them are met rarely enough to have most pilots forget about their importance [9] . Successfully retrieving these rules from long-term memory depends on the available mental resources and the evaluation of the conditions of transitions depend on the accuracy of the pilot's belief.

Moreover, a human operator does not monitor important variables with a fixed time step unless it is part of a given procedure. To determine when a variable has to be re-observed, we use heuristics based on the relative changing rate of the variable and related decision thresholds.

Thousands of hours of flight operation have an unconscious impact on pilot's knowledge and understanding of the aircraft and this is particularly remarkable when it comes to the knowledge of complicated automated flight systems such as autopilot's modes. This alteration of knowledge can be captured by the concept of Hebbian Learning [1,2] based on the Hebb's rule known as a reference to explain synaptic plasticity. This works allows the modeler to integrate Javaux's methodology [9] and account for implicit knowledge alteration although different parameters involved in Hebb's rule still need to be calibrated with real data.

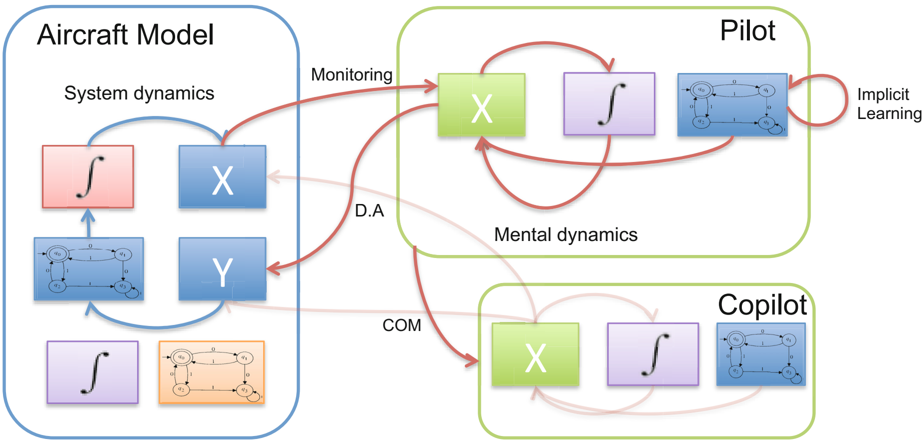

Fig. 3. Overview of the interactions between an aircraft model and a human agent enhanced with mental model capabilities. D.A stands for decision actions, they modify the configuration of the system based on the perceived state of the world. Red arrows represent units of mental activity that contributes to saturate the operator's workload capacity.

5 Conclusion

The implementation of situation awareness capabilities and mental models into WMC is being tested on a case study using the work model initially described in [11,10,6]. This work model simulates air traffic and flight deck operations and communications along the Standard Terminal Arrival Route at the airport LAX and instantiates agents such as the pilot, the co-pilot, air traffic controllers and automation agents. Monitoring patterns and approach procedures were also implemented and the pilot received a basic training on flight dynamics. At this stage of the implementation, the approach scenario exclusively uses the automated flight management system and the pilot remains in a monitoring role.

We can still analyze the evolution of the situation awareness as a result of the monitoring rate and basic internal dynamics which are key parts of the mental model. A quantitative analysis of implicit learning will be part of a future work involving realistic flight scenarios and a complete implementation of the different flight modes.

References

Bi, G., Poo, M.: Synaptic modifications in cultured hippocampal neurons: dependence on spike timing, synaptic strength, and postsynaptic cell type. The Journal of Neuroscience 18(24), 10464–10472 (1998)

Dayan, P., Abbott, L.: Theoretical neuroscience: computational and mathematical modeling of neural systems. Philosophical Psychology 15(4) (2002)

Doyle, J., Ford, D.: Mental models concepts for system dynamics research. System Dynamics Review 14(1), 3–29 (1998)

Endsley, M.R.: Toward a theory of situation awareness in dynamic systems. Human Factors: The Journal of the Human Factors and Ergonomics Society 37(1), 32–64 (1995)

Endsley, M.: Situation awareness global assessment technique (sagat). In: Proceedings of the IEEE 1988 National Aerospace and Electronics Conference NAECON 1988, pp. 789–795. IEEE (1988)

Feigh, K.M., Gelman, G., Mamessier, S., Pritchett, A.R.: Simulating first-principles models of situated human performance. IEEE Transactions on System Man and Cybernetics: Part A (Submitted June 2012)

Forrester, J.: Industrial dynamics, vol. 2. MIT Press, Cambridge (1961)

Forrester, J.: Counterintuitive behavior of social systems. Theory and Decision 2(2), 109–140 (1971)

Javaux, D.: A method for predicting errors when interacting with finite state systems. how implicit learning shapes the user's knowledge of a system. Reliability Engineering & System Safety 75(2), 147–165 (2002)

Kim, S.: Model-based metrics of human-automation function allocation in complex work environments (2011)

Pritchett, A., Kim, S., Kannan, S., Feigh, K.: Simulating situated work. In: 2011 IEEE First International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA), pp. 66–73. IEEE (2011)

Vicente, K.: Cognitive work analysis: Toward safe, productive, and healthy computer-based work. Lawrence Erlbaum (1999)