# A Framework for Task Accomplishment Using an ACT-R Simulation

**Michael Beckmann, Ulaş Yılmaz, Gloria Pöhler & Anne Wegerich**
**({mbe, uyi, gpo, awe}@mms.tu-berlin.de)**
Chair of Human-Machine Systems, Department of Psychology and Ergonomics,
Technische Universität Berlin, Franklinstr. 28/29, 10587 Berlin

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## Motivation

Modern business concepts, like *Industrial Product-Service Systems* (IPS²) (Meier, Roy, & Seliger, 2010), pose greater demands on human operators for managing and maintaining the involved technical systems. A missing assistance application to counteract this change leads to an increase in operator errors and a decrease of the overall robustness of the socio-technical system.

Cognitive architectures, like ACT-R (Anderson et al., 2004), provide the possibility of a human centered and perfect modeling of task accomplishments. This allows the prediction of steps in a process with high risks for human mistakes, as well as the recognition of human mistakes. Furthermore motion capture systems (Bregler, 2007) and advances in the field of machine learning and action recognition can provide additional (real-time) information about human interaction. To ensure an optimal production cycle the factory machinery is equipped with additional sensors. The sensory information is used to predict machine failure to schedule maintenance task in advance, before the machine breaks down.

Thus, real-time simulation of a cognitive model with access to the state space of the technical system and knowledge about human action can predict risks within a task and is able to recognize invalid execution paths. The description of the observed mistake or of a high risk situation allows an increase of the robustness of the overall system, which is the goal of subproject B5 of the Collaborative Research Center Transregio 29.

In this article we introduce a simple and effective realization of a more complicated interactive warning framework, in order to avoid operator mistakes during maintenance.

## Framework

To optimize the robustness of socio-technical systems the framework consists of a module for the cognitive model (ACT-R), which enables real-time simulation of the accomplishment of a task with respect to human parameters. This module receives information about the state space of the involved technical systems from a technical module. Information about human actions is provided by a gesture module. The cognitive module evaluates the information of the other data sources to determine valid execution paths. If a deviation from expected human actions is observed and for each a report is generated.

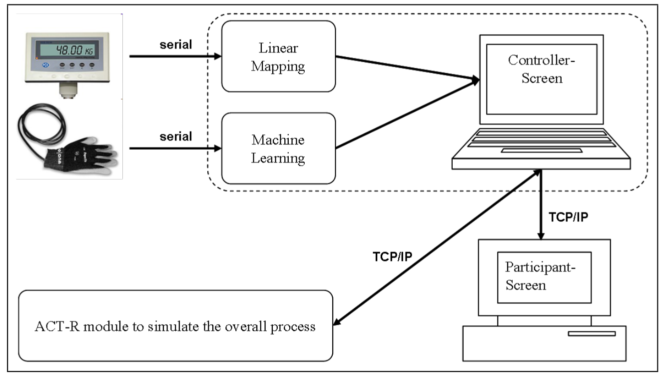


Figure 1: Overall system setup

This article describes an initial version of the framework. The modeled task is to reach a given target weight by putting several interaction objects with different shapes and weights on an electronic scale. This task is based on the experiment by Lovett, John, and Anderson (1996).

### Data and Input

The three input sources of the test setup are illustrated in Figure 1: a scale, a data glove and an expert to validate the gestures of the participants in a Wizard-of-Oz manner. The scale is a *PCE-TS* platform scale that has an RS-232-interface and a capacity of 60kg x 5g (PCE Instruments UK Ltd., 2011). The current object put on the scale is recognized by a linear mapping procedure using the known real weights of the objects. The real weight of the object is then mapped to a virtual weight the participant sees on his screen. The objects under consideration and the appropriate gesture for holding these objects are shown in Figure 2.


Figure 2: Objects, their weights and the corresponding hand gestures while holding each one of them

Hand movements are recorded using an *X-IST Wireless DataGlove* that is equipped with tilt and bend sensors (X-IST Data Glove, 2008): two sensors on the thumb and three on each of the remaining fingers. Hand gestures are then detected by measuring the relative bend of these sensors at the finger joints. The gesture recognition module normalizes the data from the data glove to account for inter-individual differences. Afterwards the module classifies the data using a supervised machine learning algorithm into one of the three hand gestures each of which corresponds to the grabbing of a weight (See Figure 2).

## Simulation

The ACT-R simulation enables the identification of operator mistakes during a task. It incorporates state space information of the technical system and gestures by the subject for rule selection. The simulation displays a warning only when a subject executes an invalid gesture during the experiment in order to be less intrusive.

The simulation considers all non-circular valid execution paths for solving the task up to the next expected gesture. All these paths are in a conflict set until the gesture module resolves the conflict by providing information about the next gesture performed by the subject. When the observed gesture is in the conflict set the simulation continues, otherwise an error report is generated and the simulation waits for a correction by the subject. The incorporation of preparatory gestures enables the recognition of an invalid action before it impacts the system state. In this case the preparatory gesture is the grasping of a weight and the system state equals the weight on the scale.

In our setup, the overall task is subdivided into three phases, as illustrated in Figure 3. The first phase deals with the identification of the weight of each interaction object. In this stage, both the human and the model try to identify the weight of each interaction object. In the second phase, subjects are asked to select one out of two strategies to reach the given target weight. In the "overshoot" strategy, the target weight can be achieved by starting with a bigger weight and subtracting all following weights from it. The second strategy is referred to as "undershoot" strategy, in which the subject starts with a weight smaller than the desired one and add all following interaction objects, so that the sum of them matches the given target weight. In the third phase, the subjects place the remaining interaction objects on the scale according to their chosen strategy to reach the target weight. An improper action in the sense of this simulation is the selection of a strategy or weight which does not lead to the solution of the task.

## Conclusions and Future Work

In this article we described an interactive warning framework. With this framework operator mistakes are detected online and task accomplishment is ensured. Participants are asked to reach a given target weight on an electronic scale using different interaction objects. Gestures of the participants are

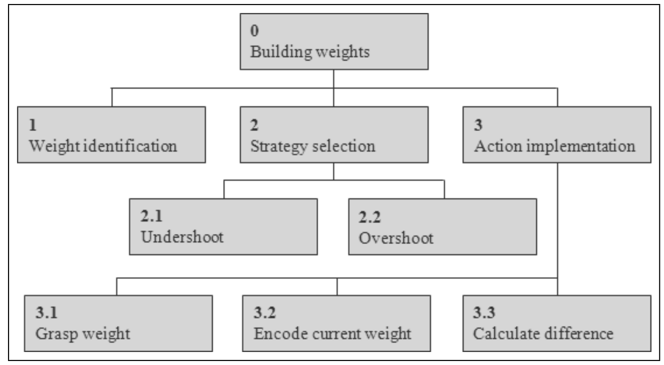


Figure 3: ACT-R tree diagram of the human events

detected using a data glove. These actions are validated by an ACT-R simulation that raises warnings in case of invalid execution paths.

A next step in the development of the framework is to test more complex technical systems and user interactions found in IPS² scenarios. The consideration of all valid execution paths is a deviation from the human decision making and poses a problem when the simulation should consider errors due to memory degradation. In this case all valid execution paths can be calculated by cloning the simulation when several rules can be selected which do not contain observable actions. The conflict resolution set is constructed from all concurrent simulations. Simulations which are not consistent with observed user behavior are discarded. An incorporation of the machine learning module into an ACT-R motor module enables the simulation to incorporate execution times for various actions. This allows the simulation to generate reports when no activity is observed, which can be interpreted as uncertainty of the operator.

## References


Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004, October). An integrated theory of the mind. *Psychol Rev*, *111*(4), 1036–1060.

PCE Instruments UK Ltd. (2011). *Platform balance pce-ts series.* Retrieved February 21, 2012, from `http://www.industrial-needs.com/technical-data-scales/platform-balance-pce-ts.htm`

Bregler, C. (2007, nov.). Motion capture technology for entertainment [in the spotlight]. *Signal Processing Magazine, IEEE*, *24*(6), 160 -158.

Lovett, M. C., John, & Anderson, R. (1996). History of success and current context in problem solving: Combined influences on operator selection. *Cognitive Psychology*, *31*, 168–217.

Meier, H., Roy, R., & Seliger, G. (2010). Industrial product-service systems - ips² . *CIRP Annals - Manufacturing Technology*, *59*(2), 607 - 627.

X-IST Data Glove. (2008). *X-ist data glove - virtual reality glove.* Retrieved February 21, 2012, from `http://www.vrealities.com/x-ist.html`