Parameter Exploration and Virtual Environment as Tools to Man-Machine Design

Florian Focone
Scalian R&D
44800, Nantes, France
focone.florian@scalian.com

Thomas Huraux
Scalian R&D
33185, Bordeaux, France
thomas.huraux@scalian.com

Résumé

Les facteurs humains prennent une importance croissante dans la conception de nouveaux environnements de travail afin d'en améliorer l'efficacité et les conditions de travail des opérateurs. L'absence de modèles numériques pour faciliter, accélérer et fiabiliser la conception nous a conduit à créer et à valider un modèle de l'humain à l'aide de mesures écologiques. Cet article propose une approche novatrice basée sur l'exploration de paramètres et la réalité virtuelle (VR) pour améliorer les environnements de travail. Dans le contexte industriel, l'application de notre travail vise à faciliter l'acceptation des opérateurs par le biais d'une démarche centrée utilisateur et d'améliorer la conception des environnements de travail.

Mots Clés

Conception centrée utilisateur; Modélisation de l'humain; Réalité virtuelle

Abstract

Human factors are becoming increasingly important in designing new working environments to improve operator's performances and working conditions. The lack of digital models to facilitate rapid, cost-effective and reliable implementation in industry led us to create and validate a model with human measures. This paper proposes a new approach based on parameter exploration and Virtual Re-

Figure 1: Screenshot of our VR app created in Unity

ality (VR) experiment to enhance "users" (*i.e.* workers) activity. In the industrial context, the application of our work aims to facilitate user's acceptance through processes of self-involvement and to improve the design of work environments in an efficient, cost-effective and reliable way.

Author Keywords

Human-Centered Design; Digital Human Modeling; Virtual Reality

ACM Classification Keywords

H.1.2 [User/Machine Systems]: Human factors, Human information processing; I.6 [Simulation and modeling]: Model Validation and Analysis, Model Development.

Introduction

Digital human modeling is of major interest for workplace design. It enables less iterations in the design process and therefore makes developments cost-effective [18]. Most of the market solutions focus on biomechanical aspects and only a few consider the cognitive aspects. Cognitive models are in fact complex and extremely difficult to validate [12] due to the inferred aspect of human cognition [7]. Based on these assessments, we present our method encompassing the development of a cognitive model of human attention and its evaluation thanks to a VR experiment.

Digital human cognitive model

Human performance predictions are connected to attention and workload [13]. Stressors, such as time pressure and mental workload have a well-known negative impact on the situation awareness and therefore on the performance [4]. The attention process has been linked to the situation awareness which is conceptualized as the difference between task demands and individual resources and capabilities [10]. Indeed, humans have a limited amount of attentional resources that can be allocated during a task [15]. Some authors have defined attention as a computational equation (*e.g.* the SEEV model) [14]. These kind of cognitive submodels can be implemented to digitalize human behaviour. A reference example is the Man-Machine Integration Design and Analysis System (MIDAS) [5] which links the attention process, the human performance and the workload. As far as we know, this model created for aeronautical purposes is the most reliable because of its validation and widespread usage in the literature. Based on a combination of modules (perceptive, attentional, memory and selective attention), the MIDAS model produces outputs such as the situation awareness, the vulnerability to human error and the human performance. It is worth remarking that other models such as Utasimo [1] have also investigated human information processing by estimating the user's mental workload.

Virtual reality as a tool to evaluate human

Based on the literature, there appears to be a cyclic relationship between the human modeling and the human-centered experience according to the goals of simulation in order to validate models [8]. For example, if the aim is to predict human performance as function of the attention, then evaluation requires to test the responses of users according to several levels of attention and to retrieve the associated performance. In this context, VR offers these possibilities by allowing to manipulate precisely the environmental variables without placing the user in danger or requiring expensive protocols. Recent technological advances allow Head-Mounted Display (HMD) to be affordable and practical. Moreover, today's modern 3D engines, such as Unity 3D, allow fast prototyping of virtual environments with excellent rendering performance. VR have also already proved relevant in the evaluation of cognitive states (*e.g.* workload, commitment, distraction). In addition, such evaluations can be associated with physiological variables (*e.g.* Electroencephalogram (EEG), Electrocardiogram) [3, 6] and behavioural measures (*e.g.* eyetracking) [17].

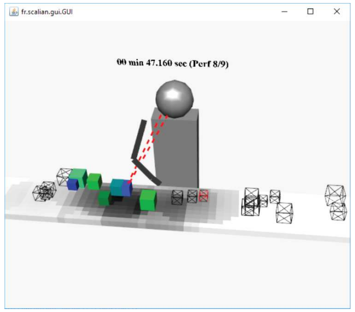

Figure 2: The artificial operator in our simulator.

Method

The research goal is to model attention associated with human response to proactively enhance human performance according to specific workplace characteristics. In the present paper, we illustrate this goal and validate our model through a virtual reality experiment. We hypothesize that the attention is sufficient to predict human performance on the task that does not require other cognitive processes (*e.g.* memory, learning, reasoning). This section briefly describes our methodology and associated tools : 1. A digital human model which features visual attention module exploring the impact of workplace. 2. A VR environment to compare the artificial operator performance with the real human performance.

Technical details The simulator is written in Java. The simulated period is 120 seconds (2 minutes) with a timestep length of 20 milliseconds. The simulations were performed in a few days on a standard Intel Core i7-7700 CPU 2600k 3.60GHz with 8GB of RAM.

Parameter exploration

We created an artificial operator to test different workplace's and operator's parameters (see Fig. 2). We then selected 5 parameters for the exploration as follows : $P1_{wp}$ the probability that an object must be sorted ; $P2_{wp}$ the rate of appearance of objects (objects per second) ; $P3_{wp}$ the speed of the conveyor belt (meters per second). $P1_{op}$ the speed of the operator's arm (meters per second) ; $P2_{op}$ the time required to distinguish a faulty object (in second) ; To cover the parameter space, we performed about 750,000 simulations.

The arm's movements were calculated using the Caliko[1] library which is a Java implementation (under free license MIT) of the FABRIK inverse kinematics algorithm [2]. Each object moving on the conveyor belt has attention score according to its characteristics (*i.e.* color, shape, rarity of appearance) and its distance relative to the operator's body. The score is given using the selective attention equation [14].

We then used a potential field method using Gaussian kernel functions to aggregate attention scores of objects and to highlight areas on the conveyor belt (Fig. 2 - black zone) that attract attention the most. The gaze direction of the simulated operator (Fig. 2 - red dotted lines) is calculated according to potential field maximum.

A focus area centered onf a maximum of attention is calculated on the conveyor belt. All the objects in this zone accumulate the attention's time needed for the recognition (or not) of an anomaly. Finally, an object of interest identified as abnormal triggers operator's arm to reach and remove it from the conveyor belt. As the object continues to advance, it may become unreachable and the operator will then search for a new object to sort.

Virtual environment

We designed a VR experiment (see Fig. 1) to measure the human performance. Ten right-handed participants (3 women and 7 men), aged from 22 to 35 (M $=$ 30.4 and SD $=$ 4.2) have taken part in the study. We used a HMD-based device (the HTC-Vive) which is an inexpensive headset (about 500$) with a 110° diagonal field of view and a maximum resolution up to 1280×1200 pixels per eye. The HTC-Vive was associated with remote controllers allowing interaction. At the beginning of the experiment, the instructions, the characteristics of the task and the risk of motion sickness were explained to the participants. The goal of the task was to sort 3 types of objects with specific meshes and textures (see Fig. 1). Participants started with a 3 minutes practice time allowing them to learn how to discriminate

[1] https://github.com/FedUni/caliko

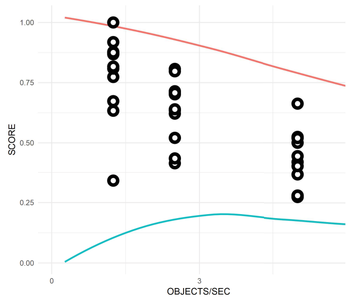

Figure 3: Performance of VR subjects (black circles) in confidence interval of simulation (max. in red and min. in blue)

Remark Exploration parameter also contributes to the control of the validity of the models used. Thus, we can check both the credibility and the stability of the results produced. In fact, even if the models used to create our artificial operator have been individually validated, the mixed-model assembly must be validated as well. This is one of the reasons why parameter exploration is a crucial step in our method.

the objects of interest and complete the task. Then, participants performed the sorting task in 3 different attention conditions, lasting 2 minutes each (in randomized counter-balanced order). Each condition corresponded to a specific appearance frequency of objects (1.25, 2.5 and 5 objects/s) while the number of objects to sort (*i.e.* to put in the trash bin) remained constant at 0.5 objects/s for all 3 conditions. For each condition and each participant, the number of objects of interest correctly placed in the trash bin, the number of objects mistakenly placed in the trash bin and the number of missed objects were logged.

Results

The results obtained in simulation with the artificial operator allow us to explore the influence of the five parameters on the performance. In fact, parameter exploration results not only allow us to relate them with the performance but also to elicit task characteristics and to better understand human activity. For instance, Fig. 4 shows heat maps of operator's performance ordered by level of task difficulty (which is basically a linear combination of $P2_{wp}$ and $P3_{wp}$) . For each value of the $P1_{op}$ and $P2_{op}$ parameters, a coloured square gives the value of the average score obtained in simulation. Each heat map represents the results for a given level of difficulty. Note that when the task is not difficult (few objects and a slow conveyor belt), the performance of the artificial operator depends essentially on its speed (*i.e.* arm motion). However, for a very difficult task (many objects and a fast conveyor belt) the performance will mainly depend on the time required by the operator regardless an object if abnormal or not.

By aggregating the different scores obtained with all simulations as a function of the difficulty, it is possible to form an estimated confidence interval of the virtual operator's performance (see Fig. 3). In order to compare and validate our model, we plot on the same graph the performances of participants measured in the VR experiment. The amount of experimental data falling within the confidence interval fitted from parameter's exploration gives an insight into the model's performance.

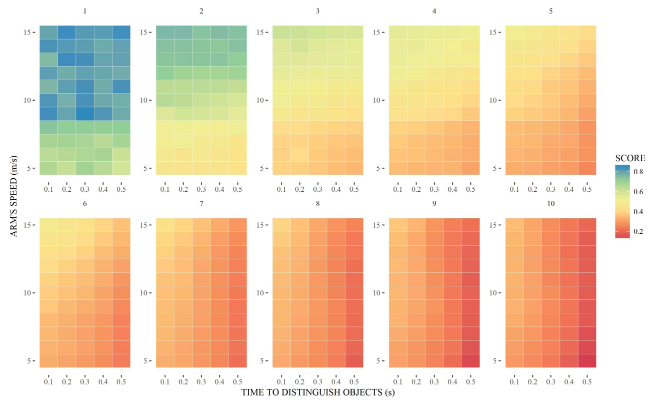

Figure 4: Operator's performance by level of difficulty (1-10)

Discussion

In this work, we developed a digital model of "users" (*i.e.* workers) focused on attention. Our methodology combines digital human models with a VR experiment. We did a parameter exploration and we compared the performance inferred from our simulations and the one gathered in a VR experiment. It has been acknowledge in the literature, that such a human-centered (or human-in-the-loop) approach does facilitate new improvements over existing solutions and leads to positive changes in the workspaces [9]. As far as we know, our work is one of the first attempts in studying the same task both in VR and with intensive simulations in order to analyse dynamic parameters effects of workplace and user characteristics on human performance.

Obviously, the validation of the models with ecological data remains an important challenge. The indirectly observable aspects of the cognitive processes tend to make difficult the comparison and the interpretation of the results [5]. In our experiment, we abstract the attention process with a performance measure by choosing a task (*i.e.* to sort objects on conveyor belt) directly linked to attention and not linked to memory or another cognitive processes. In the literature, the most known digital human model (MIDAS) produces human performance and workload as outputs. This reference human model developed by the Nasa teams is currently used by famous researchers in the aeronautical field [16, 11]. The MIDAS model and its cognitive submodels (*i.e.* Early Attention Information Salience and SEEV Visual Attention) were statistically validated in a number of experiments (see [16] for a review). The validation process makes use of data gathered from independent experiments where tasks and interfaces were reproduced in simulation. In these studies, correlations are significant but they often lack ability to generalize to other tasks, interfaces or scenario. Others authors [3] have thus proposed to validate their model by using usability evaluation methods. However, these validations do not allow to simulate changes in the interface's design nor to explore its parameters for improvement. It may be theoretically possible but it would be time-consuming and difficult to implement every interfaces to cover all possible variations in order to test the potential of each one. These frameworks are therefore not suited for such explorations. Our digital model has been used in more than 750,000 simulations modifying both workplace and artificial user characteristics. It produced a confidence interval of the performance in which data from RV experiments can be mapped relatively well. Nevertheless an accurate measure of attention (*i.e.* through EEG signals or eye-tracking), instead of being inferred as is our case, would potentially reduce the standard deviation of human measures and will allow to refine the confidence interval of our model. As we already say, one of the problems for developing cognitive model is the abstract nature of it [18]. It would be interesting to compare attention computed in simulation with real measure of visual attention. Indeed, the possibility to track eyes in HTC-Vive HMD in VR environment has become available due to very recent developments [17]. It will allow us to further validate our module in upcoming developments.

Attention is one of the most important submodel for human simulation which is a domain where SEEV is a well-established model.As improvement in our model we propose to continuously produce time series of salience for each object and the associated field of visual attention. As a result we obtain an artificial operator with attention awareness depending on changes in its environment. The dynamic aspect of our model could accommodate real time changes in the workplace depending on worker's capabilities and environmental characteristics.

Conclusion and futur research

This article presents the first step towards creating a methodology to continuously improve and validate human cognitive model[2]. As the results are quite encouraging, the next step will be to evaluate attention on another task to refine and generalize our model. We will also concentrate our efforts on evaluating attention more accurately with EEG signals and eye-tracking in order to replace our current indirect measure of performance. VR is a promising technology to fast prototype a future workplace and to evaluate its parameters. In the end, combining the two proposed tools in a human centric methodology will reduce the cost of improving workplaces but will also promote workers acceptance of change.

[2] A demonstration video is available at https://www.linkedin.com/feed/update/urn:li:activity:6414766919500599296

References

[1] Anastasia Angelopoulou and Konstantinos Mykoniatis. 2018. UTASiMo: a simulation-based tool for task analysis. *SIMULATION* 94, 1 (2018), 43–54.

[2] Andreas Aristidou and Joan Lasenby. 2011. FABRIK: A Fast, Iterative Solver for the Inverse Kinematics Problem. *Graph. Models* 73, 5 (Sept. 2011), 243–260.

[3] Meredith Carroll, Sven Fuchs, Angela Carpenter, and Kelly Hale. 2010. *Development of an autodiagnostic adaptive precision trainer for decision making (ADAPT-DM).* Technical Report. DESIGN INTERACTIVE INC OVIEDO FL.

[4] Mica R. Endsley and Daniel J. Garland. *Situation Awareness Analysis and Measurement*. CRC Press. Google-Books-ID: WrJGDsjJakcC.

[5] Brian F Gore. 2011. Man–machine integration design and analysis system (MIDAS) v5: Augmentations, motivations, and directions for aeronautics applications. In *Human modelling in assisted transportation*. Springer, 43–54.

[6] EJ Krizo, GF Wilson, and CA Russell. 2005. NuWAM: The development of a modular, real-time augmented cognition system. In *Proceedings of the 11th International Conference on Human-Computer Interaction*, Vol. 11.

[7] D Lämkull, Cecilia Berlin, and R Örtengren. 2009. Digital human modeling: Evaluation tools. (2009).

[8] K Ronald Laughery, Christian Lebiere, and Susan Archer. 2006. Modeling human performance in complex systems. Wiley New York, 965–996.

[9] Hideyuki Nakashima, Hamid Aghajan, and Juan Carlos Augusto. 2009. *Handbook of ambient intelligence and smart environments*. Springer Science & Business Media.

[10] Robert D. O'Donnell and F. Thomas Eggemeier. Workload assessment methodology. In *Handbook of perception and human performance, Vol. 2: Cognitive processes and performance*. John Wiley & Sons, 1–49.

[11] Kelly S Steelman, Jason S McCarley, and Christopher D Wickens. 2011. Modeling the control of attention in visual workspaces. *Human Factors* 53, 2 (2011), 142–153.

[12] Anders Sundin and Roland Örtengren. 2006. Digital human modeling for CAE applications. *Handbook of Human Factors and Ergonomics, Third Edition* (2006), 1053–1078.

[13] Christopher D Wickens. 2002. Multiple resources and performance prediction. *Theoretical issues in ergonomics science* 3, 2 (2002), 159–177.

[14] Christopher D Wickens, John Helleberg, Juliana Goh, Xidong Xu, and William J Horrey. 2001. Pilot task management: Testing an attentional expected value model of visual scanning. *Savoy, IL, UIUC Institute of Aviation Technical Report* (2001).

[15] Christopher D. Wickens, Justin G. Hollands, Simon Banbury, and Raja Parasuraman. *Engineering Psychology & Human Performance*. Psychology Press. Google-Books-ID: _rFmCgAAQBAJ.

[16] Christopher D Wickens, Becky L Hooey, Brian F Gore, Angelia Sebok, and Corey S Koenicke. 2009. Identifying black swans in NextGen: Predicting human performance in off-nominal conditions. *Human Factors* 51, 5 (2009), 638–651.

[17] Yanyu Xu, Yanbing Dong, Junru Wu, Zhengzhong Sun, Zhiru Shi, Jingyi Yu, and Shenghua Gao. 2018. Gaze Prediction in Dynamic 360° Immersive Videos. (2018), 5333–5342.

[18] Jingzhou Yang. Human Modeling and Simulation. In *Handbook of digital human modeling*. Taylor & Francis Group.