Skill level monitoring applied to AR assisted maintenance

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Abstract. This paper presents a work in progress experiment about AR assisted inspection for maintenance. The purpose of this experiment is to define a set of indicators that could help to evaluate the skill level of a user during the inspection task while using AR assistance system. The preliminary results already show that some parameters studied such as the time spent looking at the different elements can help to evaluate different type of behavior.

Keywords: Adaptive Assistance, Augmented Reality, Assisted Inspection

1 Introduction

The evaluation of skills is a main issue regarding the formation of new specialized workers in the industry. This is particularly important in sector like aircraft maintenance considering the tasks complexity and high level of quality expected in such activity. More over with the high variability of cases and situations encountered during the process that is higher than what we can find in production.

With the development of digital systems and technologies such as Augmented Reality, Virtual Reality, computer vision or big data dedicated to training or assistance for workers we need to be able to evaluate more precisely the interactions between that kind of systems and the worker's skills level. Indeed, we need in the first place to measure the efficiency of the workers on a maintenance task (we will stuck with inspection task for this study)

2 Literature Review

The most used key indicators to reach that first goal are the learning time, the process time and the number of mistakes made. Questionnaires are also useful tools to catch the feeling of the user at the end of the process and try to improve it [1].

Some studies go further placing various sensors on the user in order to get the most detail data to analyses his behavior during the task. [2] present a localization system attached the user's wrists in order to track it and the tools manipulated. The system record the time spent in pre-defined working areas and compare it to a reference time in order to determine the efficiency on the task.

Concerning the way to display the information to the user, Augmented Reality can afford a better visual representation of content than the traditional textual instructions used in maintenance today. Some studies worked to convert that kind of basic information into more intuitive format such as images, pictograms [3] or 3D models [4].

Even if many studies have already demonstrated the benefits of Augmented Reality for maintenance [5] [6], other directions have been explored to improve further the involvement of the user in the task using audio instructions or haptic feedbacks [1]. That kind of systems afford a better understanding of the environment and ease the interactions within it.

Even if it has been demonstrated that AR provide a clear and efficient help for maintenances tasks, this technology can also represent an additional workload of information for expert profiles. We can also observe that the task complexity has a great impact on the contribution of such assistance. Indeed AR based assistance systems can reduce the time spent on a complex task but also increase it on simple task as the system itself can add complexity [7]. To address this issue some studies started to work on adaptive assistance system. The user skill level is sometimes supposed to be known [8]. In this case the user identification in the system associates data describing his skills and can load the best scenario. Others go further trying to evaluate these data in real time to adjust the instructions level of detail during the process [9].

Skills are often evaluated punctually using questionnaire and skills grids or tables [10]. Auto evaluation remains the traditional way to qualify operators' skills in many fields of activity, particularly for those requiring high-qualified workforce such as maintenance or surgery. The high subjectivity of this kind of method requires a huge amount of data and participants to be enough reliable. However nowadays the trend is to exploit data provided by more digital processes in order to characterize each individual [11]. The monitoring of skills evolution is also an approach investigated by researchers. Indeed today the knowledge of skill level of an individual is most of the time evaluated every trimester or every month.

3 Experiment

3.1 Goals and objectives

The main objective of our experiment is to record different indicators that could translate the skill level of an expert on an inspection task and determine which are the most representatives. The next step will be to use this information to create area of interest directly on the inspected equipment 3D model. This constitutes the first step for the creation of a system able to capture and restitute knowledge automatically from and for the user.

The different indicators studied should also allow us to provide the most personalized and proportionate help to the user based on the deduced efficiency and ease to complete the task.

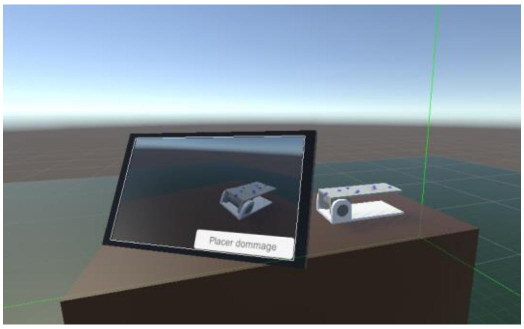
3.2 Overview

The user follows an inspection process applied to a simple numerical model presenting some damages on its surface. The goal is to identify efficiently and correctly all the damages on the little assembly. The user uses a tablet displaying AR information on the model to help him localize damages. A picking module allows him to add markers on the models where he finds a damage.

During this process, the behavior of the user is recorded through different parameters. We expect these parameters to provide some information on the user's attention evolution when going through the task.

In order to provide a better access to our solution and to capture more easily the parameters we want to analyze we design this experiment as a simulation using virtual reality. So the tablet constituting the AR assistance system is also represented in the virtual environment.

Figure 1 : Model to inspect and tablet in the virtual environment



3.3 Material and environment

The model used is a little assembly designed specifically for the experiment. The top part of the model is textured with damages (little rust stains). The experiment takes place in a virtual reality simulation. The hardware used for the VR is a first generation HTC Vive head mounted display and its controllers. The application was developed on Unity Engine and run on a desktop computer with a GTX1080 Ti GPU.

The VR scene includes the model to inspect, a workbench and a tablet. A main menu is also displayed and allow the user to switch between right-handed and left-handed mode and to skip the tutorial. At the beginning of the scenario, the model and the tablet lay on the workbench.

Tow version of the scenario have been designed : one including the AR help while the other one no. The AR help correspond to visual information in the form of little patches overlaying the model. These represent areas to inspect. They are containing at least one damage each to pick up. This help can be deactivated by clicking on the corresponding button in the tablet interface if the occlusion caused by the AR layer become a problem to clearly identify damages. The user can still reactivate the help later by clicking on the same button.

3.4 Participants

Fourteen participants participated to the experiment. Ten among them took part to the AR assisted scenario while the four remaining did not have access to this assistance. We had a variety of profiles such as students, teachers or administrative staff.

3.5 Procedure

Before the experiment, the user fills a short questionnaire detonated to better understand his background with VR technology as a previous contact with it could help him to understand quicker how to interact with the virtual environment.

The experiment starts with a tutorial phase in order to give some time to the user to better understand how to interact with its virtual environment and what we expect form him. During this phase, the model to inspect is a simple cube with two faces textures with damages. The user can manipulate the cube or the tablet with his hands. To pick up a damage the user film the cube with the tablet, align the tablet sight with the damage and click on the "place damage" button in the tablet interface. Then a little spherical marker is placed on the location aimed on the model. The user can undo this action by aiming to the marker and clicking on "delete damage" button. The user is free to end the tutorial phase when he has picked up at least one damage on the cube.

After the tutorial, the core experiment begins. The little assembly described previously replaces the cube but the task remain the same, the user must to pick up all the damages he can identify. There is total of sixteen damages to pick up on the model but the participant doesn't know that and is free to stop whenever he estimates that he have picked every damage up.

4 Preliminary results

4.1 Parameters recorded

The different parameters recorded during the experiment are the following:

- Position and rotation of the head, both hands, the tablet and the model
- The time spent manipulating the model and the tablet (independently)
- The time spent looking the model or the tablet
- The time spent aiming the model with the tablet
- The time spent using the AR help
- The number of picked up damages
- The location of each picked up damage
- The time of the core experiment (so that doesn't include the time spend on the tutorial phase)

4.2 Attention and performances

The preliminary analysis of data already shows that participants manipulated the tablet most of the time. On average, they spent more than 90% of time using it. We expected that as the tablet is used to view AR information but also to pick up damage.

Half of the participants spent approximatively the same amount of time looking to the model or looking to the tablet. For the other half we observe a greater amount of time spent looking directly to the model. They spent between 10% and 25% more time of the global duration of the core experiment.

The number of damages the participant had to identify was sixteen. Eight among them were located on the top of the model and were visible directly without the need of any manipulation whereas the eight remaining were located under the top part of the little assembly so the participant needed to do some manipulation to access them. We observe that participants spent around 15% of their time to manipulate the model but only three of them were able to find at least 80% of the damages. The average number of damages identified is 10.7 that represent .67% of the total. We also observe that participants who spend equally their time looking to the model and to the tablet could find only 40% to 60% of the damages when those who spent their time looking more n of the two items were able to reach more than 90% of the damages.

4.3 Discussion

The recording of the time spent looking the different elements in the scene seems promising as it allowed to distinguish two types of behavior. Moreover, these two group of presents very different results in terms of performance.

However, other indicators as the time spent using AR could not really bring more information about the participant profile and other need to be analyzed. More information that is detailed could be extracted from the speed evolution of the moving elements present in the scene (user, tablet and model) as other studies suggest it.

5 Conclusion

This experiment is promising, as some indicators have already allowed us to identity different behavior in a population including mixed profiles. Some data remain to be analyzed more in detail to describe even more precisely the profiles identified. We also want to point out that we still need to find an equivalent set up to move from the VR simulation to the real AR environment.

Finally, it could be interesting to measure the most relevant indicators in a population with skill levels already known and containing some expert on the task evaluated in order to check if these indicators can really be used to categorized skill levels.

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