Continuous Evaluation in Training Systems Based on Virtual Reality Using Fuzzy Rule Based Expert Systems

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Abstract *— The approach of continuous evaluation is an important tool in the learning process. However, only recently it was applied in training based on virtual reality. This paper presents a methodology of evaluation that uses the continuous evaluation approach to create an user profile from his several training. This information can be used to improve the user performance in the execution of the task. The methodology proposed is given by the union of classical statistics tools, fuzzy measures and a fuzzy rule based expert system (FRBES) to construct an individual profile for each trainee. Statistical tools, fuzzy measures and specific data of training provide information to the FRBES for the profile composition throughout training process. This new approach is a diagnostic tool that enables a trainee to understand the areas in which he presents difficulties and to concentrate to solve them.*

Index Terms — Continuous evaluation, fuzzy rule based expert system, statistical measures, fuzzy measures.

INTRODUCTION

The researches in training evaluation based on virtual reality (VR) [Burdea,2003] are recent. The first evaluation systems proposed were offline [Burdea,1998], in which a training based on VR was record in videotapes for post-analysis by experts. Recently, online methods were proposed by [Machado,2000], in which the evaluation is performed during the training process and the user receive that evaluation immediately after of the end of training. After that, several papers were produced in that subject [Machado2008 Machado,2009 McBeth,2002 Moraes2003a Moraes2003b Moraes,2004 Moraes,2005a Moraes,2008 Pucel,2003 Moody,2002 Morris,2006]. However, all those methodologies did not use any technique of continuous evaluation to improve trainee performance.

Continuous evaluation is a good tool used in present and distance learning to help the construction of the knowledge and the cognitive training [Aalsvoort,2002 Galef,1995]. In our case, the goal is to construct a diagnostic to help trainees to understand their difficulties. The first methodology was proposed only in 2005 by [Moraes,2005b], where the goal was to construct a profile to help trainees to understand their difficulties and to improve their performance. The methodology was able to provide an Evaluation Report and a Continuous Evaluation Report, showing the performance of trainee in the last training and in all trainings performed by him/her, respectively.

In this paper, we propose a new conception of continuous evaluation to construct a trainee profile from his/her several trainings and to help him/her to improve his/her performance [Arter,2000 Carlson,2003]. The union of statistical tools for measure observed variables during training and fuzzy tools for measure imprecise variables compose inputs for a fuzzy rule based expert system (FRBES) [Zadeh,1988]. The FRBES combines logically all information about fuzzy and non-fuzzy (statistical) variables for decision making about complex conjectures [Dubois,1980] and is able to construct a trainee profile.

THEORETICAL ASPECTS

For the reader's better understanding, we first present a short review about statistical methods, fuzzy sets and fuzzy rule based expert system.

Statistical Methods

In this paper the statistical methods used were:

- statistical measures;
- statistical tables;
- statistical graphics;
- statistical models (time dependent or not);
- statistical testing of hypotheses and
- statistical decision making.

A set of statistical measures commonly used for general purposes as mean, median, mode, standard deviation, etc. [Tuckey,1977] can be used to describe user interactions during the training. Statistical tables and graphics could be used to transmit specific information to the user to better understanding of results of his training. Besides, statistical models based on regression analysis can be used to construct models for sequences of steps in task execution [Draper,1988]. In some cases can be interesting to use statistical time series analysis to perform better statistical models using time as a variable [Box,1994]. Statistical measures and statistical parameters of models can be

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compared using appropriate statistical testing of hypothesis: nonparametric [Mood,1974] or parametric [Lehman,1975].

As results of these comparisons, we can have statistical decisions about equality or difference between parameters and a measure of probability of significance. The information synthesized by statistical measures and parameters helps to construct a profile for user and his/her evaluation report.

Fuzzy Sets

As it is possible that some variables in the training system do not present an exactly correspondence to the real world, some measures cannot be exact. Then we must use fuzzy sets to measure those variables [Dubois,1980].

In classical set theory a set A of a universe X can be expressed by means of a membership function $\mu_A(x)$, with $\mu_A: X \rightarrow \{0,1\}$, where for a given $a \in A$, $\mu_A(a)=1$ and $\mu_A(a)=0$ respectively express the presence and absence of a in A. Mathematically:

$$\mu_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$$

Zadeh [1965] introduced the fuzzy set theory in 1965. A fuzzy set or fuzzy subset is used to model an ill-known quantity. A fuzzy set A on X is characterized by its membership function $\mu_A: X \rightarrow [0,1]$. We say that a fuzzy set A of X is "precise" when $\exists\ c^* \in X$ such that $\mu_A(c^*)=1$ and $\forall c \neq c^*$, $\mu_A(c)=0$. A fuzzy set A will be said to be "crisp", when $\forall c \in X$, $\mu_A(c) \in \{0,1\}$.

The intersection and union of two fuzzy sets are performed trough the use of *t-norm* and *t-conorm* operators respectively, which are commutative, associative and monotonic mappings from $[0,1] \rightarrow [0,1]$. Moreover, a t-norm Γ (respec. t-conorm $\perp$) has 1 (respec. 0) as neutral element (e. g.: $\Gamma = min$, $\perp = max$) [Dubois,1988]. Thus, we can define intersection and union of two fuzzy sets as:

The intersection of two fuzzy sets A and B, with membership functions $\mu_A(x)$ e $\mu_B(x)$ is a fuzzy set C with membership function given by:

$$C=A \cap B \Leftrightarrow \mu_C(x)= \Gamma\{\mu_A(x),\mu_B(x)\},\ \forall x \in X. \qquad (2)$$

The union of two fuzzy sets A and B, with membership functions $\mu_A(x)$ e $\mu_B(x)$ is a fuzzy set C with membership function given by:

$$C=A \cup B \Leftrightarrow \mu_C(x)= \perp\{\mu_A(x),\mu_B(x)\},\ \forall x \in X. \qquad (3)$$

The complement of a fuzzy set A in X, denoted by $\neg A$ is defined by:

$$\mu_{\neg A}(x) = n(\mu_A(x)),\ \forall x \in X. \qquad (4)$$

where: $n: [0,1] \rightarrow [0,1]$ is a negation operator which satisfies the following properties:

- n(0)=1 and n(1)=0
- n(a) ≤ n(b) if a>b
- n(n(a))=a, ∀ x∈ [0,1]

and a negation is a strict negation if it is continuous and satisfies

- n(a)<n(b) if a>b.

The main negation operator which satisfies these four conditions is $n(a) = 1-a$.

The implication function between two fuzzy sets A and B, with membership functions $\mu_A(x)$ e $\mu_B(x)$, is a fuzzy set C with membership function given by:

$$C=A \Rightarrow B \Leftrightarrow \mu_C(x,y)= \nabla\{\mu_A(x),\mu_B(y)\},\ \forall x \in X,\ \forall y \in Y \quad (5)$$

where $\nabla: [0,1]^2 \rightarrow [0,1]$ is an implication operator which obeys the following properties: $\forall a, a', b, b' \in [0,1]$:

- If b ≤ b' then ∇ (a,b) ≤ ∇ (a,b');
- ∇ (0,b)=1;
- ∇ (1,b)=b.

The pure implications obeys too:

- If a ≤ a' then ∇ (a,b) ≥ ∇ (a',b);
- ∇ (a, ∇ (b,c))= ∇ (b, ∇ (a,c)).

Fuzzy Rule Based Expert System

Expert systems [Rich,1993] use the knowledge of an expert in a given specific domain to answer non-trivial questions about that domain. For example, an expert system for image classification would use knowledge about the characteristics of the classes present in a given region of the image to classify a pixel of that region. This knowledge also includes the "how to do" methods used by the human expert. Usually, the knowledge in an expert system is represented by rules in the form:

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IF <condition> THEN <conclusion>.
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Most rule-based expert systems allow the use of connectives AND or OR in the premise of a rule and of connective AND in the conclusion. From rules and facts, new facts will be obtained through an inference process.

In several cases, we do not have precise information about conditions or conclusions, then the knowledge in the rules cannot be expressed in a precise manner. Thus, it can be interesting to use a fuzzy rule-based expert system [Zadeh,1988].

An example of a simple fuzzy rule could be:

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IF <access to the help is persistent>
    THEN <user is Novice>.
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where "persistent" can be characterized by a fuzzy set.

METHODOLOGY

According to [Moraes,2005b], a tool for continuous evaluation must be interconnected with an online evaluation system and must receive information from it about all variables of interest. An evaluation system works near a virtual reality simulator. In general, an on-line evaluation system should be capable to monitor user interactions while he operates the simulation system. For that is necessary to collect the information about positions in the space, forces, torque, resistance, speeds, accelerations, temperatures, visualization and/or visualization angle, sounds, smells and etc. These information will be used to feed the evaluation system. In the Figure 1 [Moraes2003b] we can observe that the virtual reality simulator and the system of evaluation are independent systems, however they act simultaneously.

The user interactions with the system are monitored and the information are sent to the evaluator system that analyzes the data and it emits an Evaluation Report about the user performance at the end of the training according pre-defined classes of performance. A set of rules of the fuzzy based rule expert system (FRBES) [Zadeh,1988] defines each one of the possible classes of performance, which are defined from specialists knowledge. The interaction variables will be monitored according to their relevance to the training. This way, each application will have their own set of relevant variables that will be monitored [Moraes2003b].

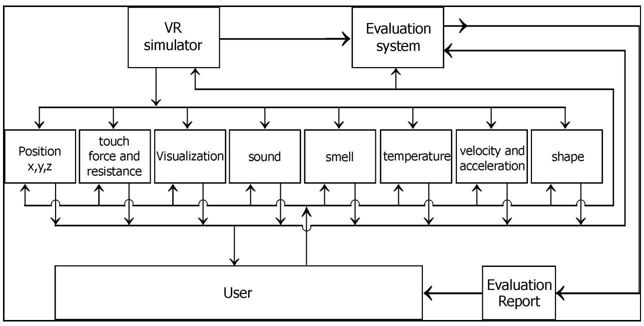

FIGURE 1.
DIAGRAM OF A VIRTUAL REALITY SIMULATOR WITH AN EVALUATION SYSTEM.

If the same user has performed other trainings, the Continuous Evaluation Tool uses data collected from user interaction in his/her several training to create an User Profile to construct a Continuous Evaluation Report about all set of training. That information is used to evaluate the trainee and can improve his/her performance in real tasks [Sternberg,2001]. The Figure 2 [Moraes,2005b] shows a diagram of an Evaluation System able to perform continuous evaluation.

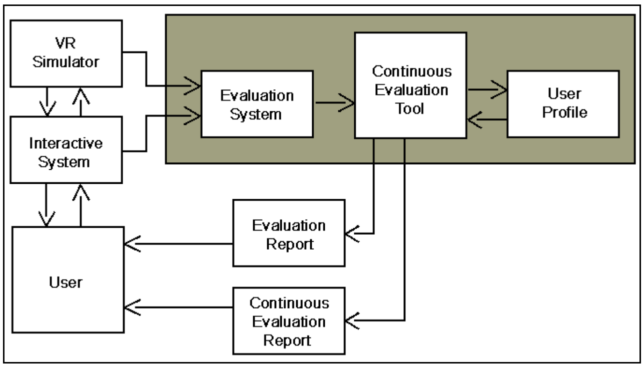

FIGURE 2.
DIAGRAM OF AN EVALUATION SYSTEM WITH APPROACH OF CONTINUOUS EVALUATION. ADAPTED FROM [MORAES,2005B].

This methodology makes a union of statistical tools, fuzzy tools and an FRBES to construct an individual profile for trainee. Statistical tools are programmed to make an automatic analysis of the database and construct statistical measures, tables, graphics [Tukey,1977], statistical models (time dependent or not) [Draper,1988 Box,1994] and results of statistical hypothesis testing [Mood,1974 Lehman,1975]. From these information (statistical measures and parameters), the FRBES can create a user profile and a continuous evaluation report. The continuous evaluation report presents the trainee profile and shows, with statistical measures, tables, graphics and models, the execution performance of specific tasks. As some variables cannot be measured with precision, Fuzzy tools are implemented to make fuzzy measures and to construct fuzzy information [Zadeh,1965]. They complement other information and are used as input for FRBES [Zadeh,1988]. Figure 3 shows the new methodology presented.

In the first time when user executes his training, the Evaluation Report emits information about the user performance, only at the end of the training, according to classes of performance previously defined. This information is stored in a User Profile for posterior evaluations with approach of continuous evaluation. In the second time when user executes his/her training, the Continuous Evaluation is able to construct a Continuous Evaluation Report, which presents information about user performance over specific tasks, using statistical measures, tables, graphics and models. Both reports present information from the last training. But, additionally, the Continuous Evaluation Report will show accumulative information about the sequence of trainings for this user.

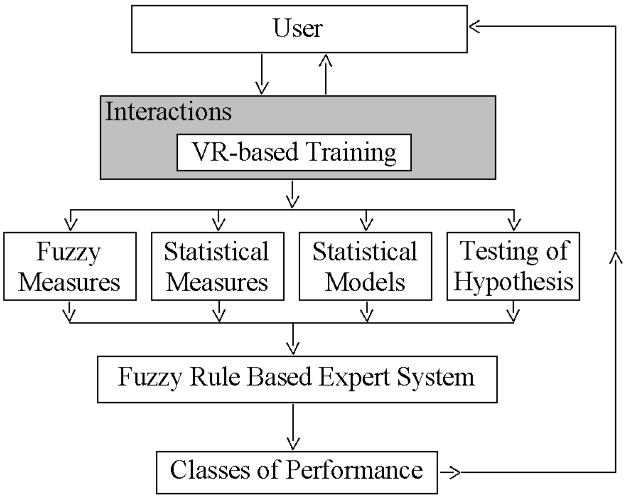

FIGURE 3.
DIAGRAM OF THE CONTINUOUS EVALUATION SYSTEM USING FRBES.

APPLICATION

This methodology can be applied for any activity, specially those who offer risks to user or to people who depends of him/her. In this context, continuous evaluation is an interesting tool to improve knowledge constructing. For example, in medical areas where invasive procedures can be simulated by VR it is necessary some kind of evaluation tool with properties of continuous evaluation. These tools are capable to show to the user his/her qualities and his/her deficiencies in the execution of a medical procedure.

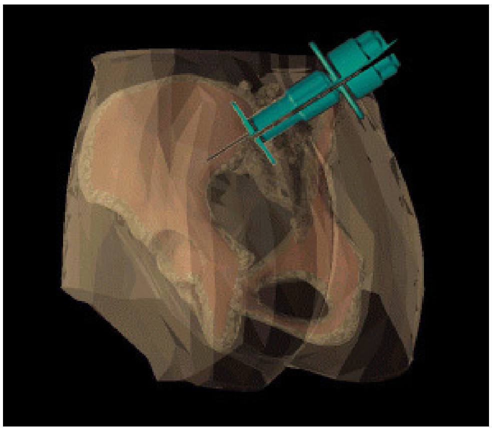

FIGURE 4.
SCREENSHOT OF THE BONE MARROW SIMULATOR WITH SEMI-TRANSPARENT VVIEW OF THE PELVIC REGION.

An example is the bone marrow simulator (Figure 4), a virtual reality simulator to training the extraction of bone marrow in children [Machado,2003]. In this application the user is a novice surgeon that must acquire dexterity to insert a needle in the pelvic region of a child and find the bone marrow, located inside the iliac bone.

As interactive tool, the user manipulates a haptic device, represented in the system by the needle. This device is responsible to provide tactile sensations and force feedback related to the manipulation of the needle in the system. Figure 5 shows the haptic device used for interaction.

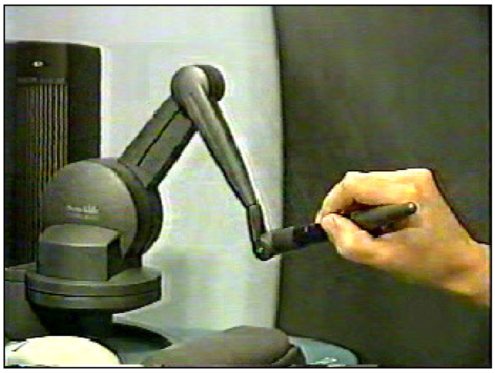

FIGURE 5.
HAPTIC DEVICE FOR INTERACTION WITH TACTILE SENSATION AND FORCE FEEDBACK.

CONCLUSIONS

In this paper we introduced a new methodology for evaluation training using the continuous evaluation approach. This methodology uses statistical measures, models and results of statistical hypothesis testing, as well as fuzzy measures, as inputs of a FRBES. This system is able to construct an individual profile for trainee and emit to him information about his performance at the end of the training, according to classes of performance previously defined, as proposed in others methodologies. Moreover, this methodology can provide to user information about his performance in specific tasks in the training.

A system developed using the proposed methodology is a diagnostic tool, which helps a trainee to understand his difficulties. From information presented the trainee can solve his difficulties and improve his performance.

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