Fuzzy Continuous Evaluation in Training Systems Based on Virtual Reality

Ronei M. Moraes[1] and Liliane S. Machado[2]

1 Department of Statistics, Federal University of Paraíba
João Pessoa/PB, Brazil
2 Department of Informatics, Federal University of Paraíba
João Pessoa/PB, Brazil
Email: ronei@de.ufpb.br, liliane@di.ufpb.br

Abstract*—The approach of continuous evaluation is an important methodology in educational learning process. However, only recently it was applied in training based on virtual reality. This paper presents a methodology of evaluation that uses a fuzzy continuous evaluation approach to provide a user profile from his several training. This information can be used to improve the user performance in the real execution of a task. The methodology proposed is given by the union of fuzzy statistical measures, fuzzy statistics and fuzzy parameters (fuzzy testing of hypothesis and fuzzy regression models) as input for a fuzzy rule based expert system (FRBES). The FRBES is able to construct an individual profile for each trainee. This new approach is a diagnostic tool that enables a trainee to understand the areas in which he presents difficulties, allowing him to concentrate on improving skills related to them.*

Keywords— Continuous evaluation, fuzzy rule based expert system, fuzzy statistics, fuzzy measures, fuzzy regression models.

1 Introduction

The researches in training evaluation based on virtual reality (VR) [4] are recent. The firsts evaluation systems were offline [3], in which a training based on VR was recorded in videotapes for post-analysis by experts. Recently, online methods were proposed by [13], in which the evaluation is performed during the training process and the user receives that evaluation immediately after the end of training. Since then, several papers were produced in that subject [9, 12, 15, 16, 18, 19, 20, 22, 24, 25, 26]. However, all those methodologies did not use any technique of continuous evaluation to improve trainee performance. Continuous evaluation is a educational methodology used in present and distance learning to help the construction of the knowledge and the cognitive training [1, 10].

In the present work, the goal is to construct a diagnostic to help trainees to understand their difficulties. The first methodology of this kind was proposed only in 2005 by [23] where the goal was to construct a profile to help trainees to understand their difficulties and to improve their performance. That methodology, based on a classical based rule expert system, 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. Morris et al. (2006) suggested the use of statistical linear regression to evaluate user's progress in a bone surgery. After that, in 2009 [17] had proposed another approach based on fuzzy based rule expert system (FRBES), using statistical measures and statistical models, statistical testing of hypothesis, as well as fuzzy measures as input for a FRBES. However, some problems had not been solved yet. The problems are related to assumptions of the statistical models and statistical testing of hypothesis, mainly the Gaussian distributions of data.

In this paper, we propose a new conception of fuzzy continuous evaluation to construct a trainee profile from his/her several trainings and to help him/her to improve his/her performance [2, 6]. In this approach we use fuzzy statistical measures, fuzzy statistics and fuzzy parameters (fuzzy testing of hypothesis and fuzzy regression models) to solve that problems with statistical assumptions. Those fuzzy parameters compose inputs for an fuzzy based rule expert system (FRBES) [30]. The FRBES combines logically all information about fuzzy statistical variables and parameters to making decisions about complex conjectures [7] and is able to construct a trainee profile.

2 Theoretical Aspects

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

2.1 *Fuzzy Sets and Fuzzy Numbers*

As some variables in the training system do not present an exactly correspondence to the real world, some measures cannot be exact. Then, fuzzy sets are used to measure those variables [7]. 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:

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

Zadeh [29] 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

ISBN: 978-989-95079-6-8

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.: $\Gamma=min$, $\perp=max$) [8]. 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:

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

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:

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

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

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

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

- $n(0)=1$ and $n(1)=0$
- $n(a) \leq n(b)$ if $a>b$
- $n(n(a))=a$, $\forall\ x\in [0,1]$

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

- If $b \leq b'$ then $\nabla(a,b) \leq \nabla(a,b')$;
- $\nabla(0,b)=1$;
- $\nabla(1,b)=b$.

The pure implications obeys too:

- If $a \leq a'$ then $\nabla(a,b) \geq \nabla(a',b)$;
- $\nabla(a, \nabla(b,c))= \nabla(b, \nabla(a,c))$.

Beyond concept of fuzzy sets and their operations, it is important to the concept of fuzzy numbers [3]. In this paper we used triangular or triangular shaped fuzzy numbers, which are defined by three real numbers $d<e<f$ where the interval $[d,f]$ is the base of the triangle and *e* is a vertex.

2.2 *Fuzzy Statistics*

In this paper the statistical methods used were:

1. fuzzy statistical measures;
2. fuzzy statistical models (time dependent or not) and
3. fuzzy statistical testing of hypotheses.

A set of fuzzy statistical measures, commonly used for general purposes as fuzzy mean, fuzzy median, fuzzy standard deviation, etc. [3], can be used to describe user interactions during the training. Besides, fuzzy statistical models based on fuzzy regression can be used to construct fuzzy models for the way followed by user in task execution [10]. This model can be done by:

$$Y = Ax_1 + Bx_2 + Cx_3 \quad (6)$$

where *Y, A, B* and *C* are fuzzy numbers and x_1, x_2 and x_3 are real numbers.
Fuzzy statistical measures and fuzzy statistical parameters of fuzzy models (as *A, B* and *C* above) can be compared with fuzzy parameters of ideal fuzzy models using appropriate fuzzy statistical testing of hypothesis from its α-cuts [3]. As results of these comparisons, we can make fuzzy statistical decisions about equality or difference between parameters using measure of fuzzy probability of significance. The information synthesized by fuzzy statistical measures and fuzzy parameters helps to construct a profile for user, his/her Evaluation Report and his/her Continuous Evaluation Report.

2.3 *Fuzzy Rule Based Expert System*

Expert systems [27] 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 to classify a pixel in an image 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 as:

```
IF <condition> THEN <conclusion>
```

Most rule-based expert systems allows 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 could be interesting to use a fuzzy rule-based expert system [30]. An example of simple fuzzy rule could be:

```
IF <access to the help is persistent>
   AND <Global Users Performance is bad>
THEN <user is Novice>.
```

where "persistent" and "bad" can be characterized by fuzzy sets.

ISBN: 978-989-95079-6-8

3 Methodology

According to [23], a tool for continuous evaluation must be interconnected with an online evaluation system and must receive information from it about all variables of interest. The evaluation system works near a virtual reality simulator. In general, an online evaluation system should be capable to monitor user interactions while he/she operates the simulation system. In order to achieve that, it 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. This information will be used to feed the evaluation system. In the Figure 1 [21], we can observe that the virtual reality simulator and the system of evaluation are independent systems, however they act simultaneously.

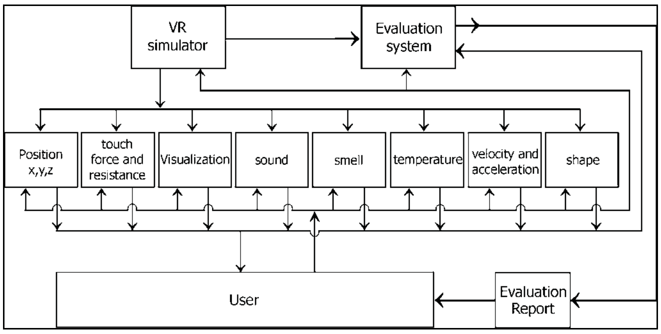

Figure 1: Diagram of A Virtual Reality Simulator With an Evaluation System.

User interactions are monitored and the information are sent to the evaluation system that analyzes the data and emits, at the end of the training, an Evaluation Report about the user performance, according *M* pre-defined classes of performance. A set of rules of the fuzzy based rule expert system (FRBES) [30] 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. Thus, each application will have their own set of relevant variables that will be monitored [21].

If the same user had performed other trainings, the Continuous Evaluation Tool uses the data collected from user interaction in his/her several training to create an User Profile and 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 [28]. The Figure 2 [23] shows a diagram of an Evaluation System able to perform continuous evaluation.

A Fuzzy Continuous Evaluation Tool makes a union of fuzzy statistical measures, models and testing of hypothesis, and an FRBES to construct an individual profile for trainee. Fuzzy statistical tools are programmed to make an automatic analysis of the database and construct fuzzy statistical measures, graphics fuzzy statistical models and results of fuzzy statistical hypothesis testing. FRBES uses this information to create a user profile and a continuous evaluation report. The continuous evaluation report presents the trainee profile and shows, with fuzzy statistical measures, graphics and models, the execution performance of specific tasks. They are used as input for FRBES [30]. Figure 3 shows the new methodology presented.

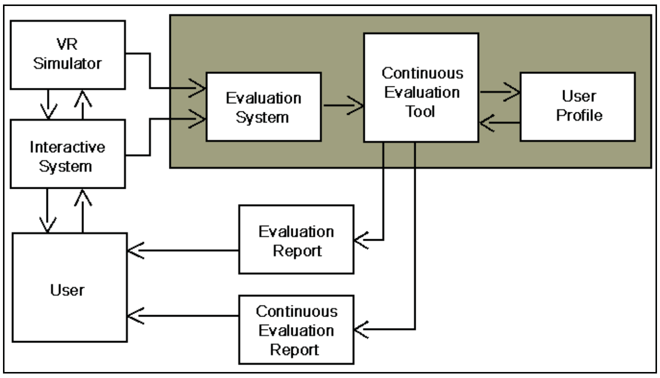

Figure 2: Diagram of an Evaluation System With Approach of Continuous Evaluation. Adapted from [23].

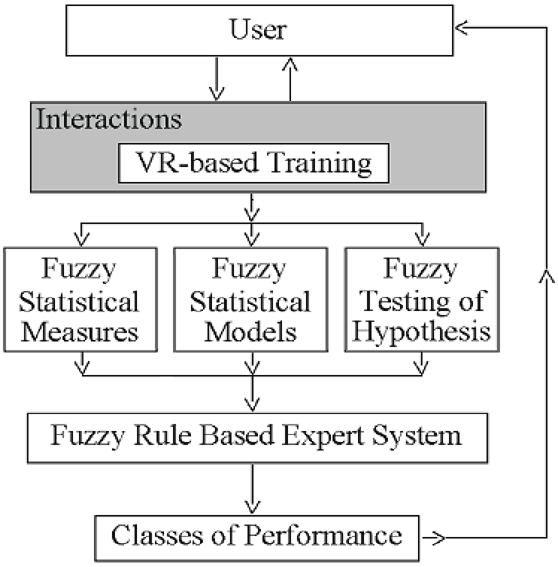

Figure 3: Diagram of The Continuous Evaluation System using FRBES.

In the first time that user executes his training, the Evaluation Report emits information about the user performance, 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 a second time when user execute his/her training, the Fuzzy 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 accumulated information about the sequence of trainings for this user.

ISBN: 978-989-95079-6-8

4 Application

This methodology can be applied for any activity, particularly those who offer risks to the user/trainee or to people who depends of him/her. In this context, fuzzy continuous evaluation is an interesting tool to improve knowledge construction. For example in medical area, where invasive procedures can be simulated by VR, it is necessary some kind of evaluation tool with properties of continuous evaluation. In those simulators, users perform realistic virtual procedures and can acquire dexterity and/or improve skills. If a continuous evaluation tool is attached to those applications, user interactions can be collected in real time to be used to evaluation since the tool can show to the user his/her qualities and his/her deficiencies in the execution of the medical procedure.

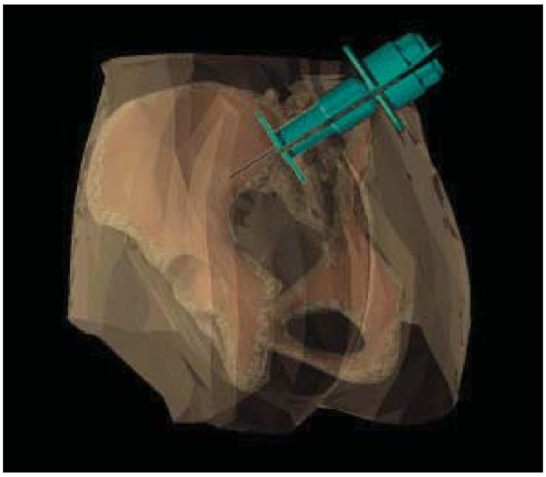

Figure 4: Screenshot of the Bone Marrow Simulator with a Semi-Transparent View of the Pelvic Region.

An example is the bone marrow simulator (Figure 4), a virtual reality simulator to training the extraction of bone marrow in children [13]. 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. The user manipulates a haptic device, a 6DOF interaction device, represented in the system by a needle. This device is responsible to provide tactile sensations and force feedback related to the manipulation of the needle in the system. With this device, the user can touch and feel the tissue properties of anatomy models, use his perception to identify bone location under the skin and penetrate the tissues to extract bone marrow. Figure 5 shows the haptic device used for interaction. In spite of Figure 4 presents a semi-transparent model, it is only for demonstration purposes. In the real bone marrow harvest procedure user cannot have internal visualization of the body and the touch sense is the only information perceived during needle penetration over 4 different properties tissue layers. Table 1 presents an example of description of each tissue layer present in the bone barrow harvest simulator. The hardness refers how much force must be applied to penetrate the tissue, the viscosity refers to how hard are the movements when inside the layer and surface friction indicates how slippery is the surface of the layer. The percentages are only an estimation of values and the calibration of the properties is done by a physician. The haptic device used in the simulation can read 1000 samples per second, including spatial position and applied forces. This data is an example of information used by the evaluation tool. After calibration and system setup, the same physician performs the simulation several times and in different ways to provide labels for each one of *M* classes of performance.

Figure 5: Haptic Device for Interaction with Tactile Sensation and Force Feedback.

Table 1: Subjective description of tissue properties for a bone marrow simulator.

Tissue	*hardness*	*viscosity*	Surface friction
Epidermis	20%	70%	60%
Subcutaneous	20%	70%	60%
Periosteum	80%	90%	20%
Hard bone	80%	90%	20%
Bone marrow	1%	5%	1%

The FRBES contains different rules to manipulate fuzzy information collected from users interaction using haptic device. The user must introduce the needle in pelvic region and go to the bone to harvest the marrow. This path can be modeled by a fuzzy regression model and the parameters of this regression can be compared with the *M* models previously stored by the physician. In the procedure, forces and torques applied through the needle are approximately constants between skin and bone. However, it is necessary to apply a different torque to introduce the needle into the bone. Fuzzy statistical parameters, as mean and standard deviation, can be used to compare this procedure with the parameters of procedure performed by physician. All those fuzzy statistical parameters can be compared with parameters of classes of performance using a fuzzy testing of hypothesis. The fuzzy probability of these comparisons and their correspondent hypothesis are used as input in the FRBES. If everything was performed correctly, an Evaluation Report is created to inform the user about it. In opposition, if something was performed wrong, the FRBES use their rule databases to find problems in execution and inform the user. Examples are presented in the following.

ISBN: 978-989-95079-6-8

4.1 *Example 1*

Let be five classes of performance done by fuzzy sets in Ω={very good, good, reasonable, bad, novice}. The fuzzy regression model for the way followed by user has parameters (for coordinates of tri-dimensional space), done by the fuzzy sets *A, B* and *C*.

Vectors of data, whose fuzzy mean and fuzzy standard deviation are given by D_{f1}, E_{f1}, G_{t1} and H_{t1}, respectively, store the force and torque applied between skin and bone. In the introduction of the needle into the bone, force and torque new vectors of data are stored, whose fuzzy mean and fuzzy standard deviation are given by D_{f2}, E_{f2}, G_{t2} and H_{t2}, respectively.

For each one class of performance, there are reference parameters for models, forces and torques. Those parameters are denoted by A^*, B^* and C^* for fuzzy models and D_{fi}^*, E_{fi}^*, G_{ti}^*, H_{ti}^* , with $i=1,2$ for forces and torques respectively. To compare those parameters with these reference parameters for each class, fuzzy statistical hypothesis testing are used and fuzzy probabilities for null hypothesis are obtained from them. These probabilities are treated by FRBES using rules as:

```
IF <Fuzzy Probability of Applied Forces in
    Phase 1 is Acceptable>
   AND <Fuzzy Probability of Applied Forces in
        Phase 2 is Unacceptable>
THEN <User Performance is bad>.
```

or

```
IF <Fuzzy Probability of A parameter in Fuzzy
    Model is Acceptable>
   AND <Fuzzy Probability of B parameter in
        Fuzzy Model is Acceptable>
   AND <Fuzzy Probability of C parameter in
        Fuzzy Model is Acceptable >
THEN <User Performance is very good>.
```

When the system classifies a user as good, reasonable, bad or novice, the FRBES can detect the user mistakes by the search for unacceptable fuzzy probabilities. From them, is possible to find where user made mistake. For example, it can be noticed the user made mistake in the application of forces in the Phase 2, but everything was performed correctly in the Phase 1.

```
IF <Global User Performance is bad >
   AND <Fuzzy Probability of Applied Forces in
        Phase 2 is Unacceptable>
THEN <Applied Forces in Phase 2 has
      Mistake>.
```

By the rule above, the user will know about his/her mistake. Also it is possible to know what was performed wrong. In this case, only three cases are possible:

1. Applied force was excessive and it was not possible to harvest the marrow.
2. Applied force was normal and it produced a good procedure.
3. Applied force was lower than normal, and the needle cannot be introduced into the bone.

The FRBES has rules to verify which situation really happened. For example:

```
IF <Global User Performance is bad >
   AND <User Applied Forces in Phase 2 has
        Mistake>
   AND <Applied Forces in Phase 2 is Excessive>
THEN <Applied Forces in Phase 2 is Upper
      than normal>.
```

4.2 *Example 2*

In the Section 4.1 it was illustrated how the Evaluation Report works. Now, we present the Continuous Evaluation Report. This report must show the evolution of user according to the sequence of training he/she performed, including the last one. The goal of this report is to help user to improve his/her performance.

Let be a training sequence for a user, denoted by $S=\{s_1,...,s_n\}$. In each s_j ($j=1,...,n$) is stored a set of vectors with: variables of training, performance by variable of training and global user performance. From this information the FRBES can produce a Continuous Evaluation Report, showing to the user his/her evolution. For example, mistakes are less frequent now than before; serious mistakes are not made there is a long time; average of the time of procedure execution is coming to ideal with small standard deviation. The rules below show how it is processed:

```
IF (<Fuzzy Correlation (serious mistakes) is
     Negative OR Approximate Zero)
    AND <Fuzzy Correlation (number of mistakes)
         is Negative OR Approximate Zero>
THEN <User’s Continuous Evaluation is Good>.
```

or

```
IF (<Fuzzy Probability of Execution Time is
     Acceptable)
    AND <Fuzzy Standard Deviation (Execution
         Time) is Small>
THEN <User’s Continuous Evaluation is Very
      Good>.
```

FRBES can evaluate the global users performance along the sequence of performed procedures. It is done by rules like this one:

```
IF <Fuzzy Correlation (Global User Performance)
    is Positive OR Approximate Zero>
   AND <The Last One (Global User Performance)
        is Very Good>
THEN <User’s Continuous Evaluation is Very
      Good>.
```

For better user comprehension of his/her situation, some graphics are presented showing all history of evaluations. For example, a graphic illustrate the number of serious mistakes or his/her Global Users Performance along the sequence of performed procedures.

5 Conclusions

In this paper we introduced a new methodology for evaluation training using a fuzzy continuous evaluation approach. This methodology uses fuzzy statistical measures, models and results of fuzzy statistical hypothesis testing, as inputs of a FRBES. This system is able to construct an

ISBN: 978-989-95079-6-8

individual profile for trainee and emit to him/her information about his/her 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 and show where the user made mistakes. The methodology was illustrated by examples to show its functionalities and how the Evaluation Report and Continuous Evaluation Report are made.

A system developed using the proposed methodology is a diagnostic tool, which helps a trainee to understand his/her difficulties. From information presented by a Fuzzy Continuous Evaluation system, the trainee can understand his/her difficulties and improve his performance.

Acknowledgment

This work is partially supported by Brazilian Council for Scientific and Technological Development, CNPq (Process 303444/2006-1) and Brazilian Research and Projects Financing, FINEP (Grant 01-04-1054-000).

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