ANOTHER APPROACH FOR FUZZY NAIVE BAYES APPLIED ON ONLINE TRAINING ASSESSMENT IN VIRTUAL REALITY SIMULATORS

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Abstract *— Training systems based on virtual reality are used in several areas of human activities. The user is immersed into a virtual world to have realistic training and realistic interactions with that world. In some kinds of training it is important to know the user's skills. An online assessment system allows to the user improve his learning because it can identify, immediately after the training, where he committed mistakes or presented low efficiency. In this paper, it was used an another approach for Fuzzy Naive Bayes proposed by Störr, for online training assessment based on a for modeling and classification of simulation in N pre-defined classes. Fuzzy Naive Bayes is a generalization of probabilistic networks, specifically Bayesian Networks, which each variable takes linguistic values and they are defined as fuzzy sets. Over them, it is computed a fuzzy partition over continuous variables.*

Index Terms — Assessment, Fuzzy Naive Bayes, Online Training Assessment, Medical Training, Virtual Reality.

INTRODUCTION

Training systems based on virtual reality are used in several areas [4]. The user is immersed into a virtual world to have realistic training and realistic interactions. However, it is important assess user's training to know the quality of his skills [3]. Several kinds of training based on VR use to record the user actions in videotapes to post-analysis by experts. In these cases, the user receives his assessment after some time [11]. In didactical terms, this is a problem because probably after some hours the user will not remember his exact actions what will make difficult the use of the assessment information to improve his performance. Besides of that, several kinds of training cannot be simply classified as bad or good due to its complexity. Then, the existence of an online assessment tool incorporated into to a simulation system based on virtual reality is important to allow the learning improvement and users assessment [10].

An online assessment system allows the user to improve his learning because it can identify, immediately after the training, where he committed mistakes or presented low efficiency. However, just a few years ago were proposed the first methodologies for training assessment. Specific assessment methodologies for training through virtual reality simulators are still more recent. Because VR simulators are real-time systems, an assessment tool must continuously monitor all user interactions and compare his performance with pre-defined expert's classes of performance. By didactic reasons, it is more interesting the use of online assessment tools due the fact that these methods allows the user to easily remember his mistakes and learn how to correct.

Some models for online and offline assessment of training have been proposed [5,7,9,11,16,18,20,21,22]. The main problems related to online training assessment methodologies applied to VR systems are the computational complexity and the accuracy. An online assessment tool must have low complexity to do not compromise VR simulations performance, but it also must have high accuracy to do not compromise the user assessment.

Some of those models, mentioned above, are based on machine learning and they use discretization of continuous variables, as proposed in [20]. Recently, the first assessment system based on Fuzzy Naive Bayes method was proposed by [23]. However, an another approach for Fuzzy Naive Bayes (FNBayes) method was proposed by Störr [29], with similar properties of Classical Naive Bayes. So, this approach can lead with main requirements of an assessmentsystem for training based on virtual reality.

VIRTUAL REALITY AND SIMULATED TRAINING

Virtual Reality refers to real-time systems modeled by computer graphics that allow user interaction and movements with three or more degrees of freedom [4]. More than a technology, virtual reality became a new science that joins several fields as computers, robotics, graphics, engineering and cognition. Virtual Reality worlds are 3D environments created by computer graphics techniques where one or more users are immersed totally or partially to interact with virtual elements. The realism of a virtual reality application is given by the graphics resolution and by the exploration of users senses. Basically, special devices stimulate the human senses as vision, audition and touch. As example, head-mounted displays (HMD) or even conventional monitors combined with special glasses can provide stereoscopic visualization, multiple sound sources positioned provides 3D sound, and touch can be simulated by the use of haptic devices [13,28].

Virtual reality systems for training can provide significant benefits over other methods of training, mainly in

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critical medical procedures. In some cases, those procedures are done without visualization for the physician, and the only information he receives is done by the touch sensations provided by a robotic device with force feedback. These devices can measure forces and torque applied during the user interaction [14] and these data can be used in an assessment [10,26]. One kind of haptic device is based on a robotic arm and provides force feedback and tactile sensations during user manipulation of objects in a three dimensional scene. This way, user can feel objects texture, density, elasticity and consistency. Since the objects have physical properties, a user can identify objects in a 3D scene without see them by the use of this kind of device [13]. This is especially interesting in medical applications to simulate proceedings in which visual information is not available. One of the main reasons for the use of robotics arms in medical applications is their manipulation similarity when compared to real surgical tools.

ASSESSMENT IN VIRTUAL REALITY SIMULATORS

The assessment of simulations is necessary to monitor the training quality and provide some feedback about the user performance. User movements, as spatial movements, can be collected from mouse, keyboard and any other tracking device. Applied forces, angles, position and torque can be collected from haptic devices [28]. Then, virtual reality systems can use one or more variables, as the mentioned above, to evaluate a simulation performed by user.

Some simulators for training present a method of assessment. However they just compare the final result with the expected one or are post-analyses of videotape records [3,11]. Recently, some models for off-line or on-line assessment of training have been proposed, some of them use Discrete Hidden Markov Models [26] or Continuous Hidden Markov Models [27] to modeling forces and torque during a simulated training in a porcine model. Machado et al. [10] proposed the use of a fuzzy rule-based system to on-line assessment of training in virtual worlds. Using an optoelectronic motion analysis and video records, McBeth et al. [15] acquired and compared postural and movement data of experts and residents in different contexts by use of distributions statistics. Moraes and Machado proposed several methods [12,17,18,20,21]. They also proposed a methodology to automatically assess a user's progress to improve his/her performance in virtual reality training systems [19] using statistical measures and models (time dependent or not) as well as a fuzzy expert system. After that, Morris et al. [24] suggest the use of statistical linear regression to evaluate user's progress in a bone surgery.

In this paper, we propose a new system for assessment based on FNBayes [29], which is described in next session. This system can perform an online training assessment for virtual reality simulators. A vector of information with data collected from user interactions with virtual reality simulator is used by the system and these data are compared by the assessment system with M pre-defined classes of performance.

To test the method proposed, we are using a bone marrow harvest simulator [11]. This simulator has as goal to training new doctors to execute the bone marrow harvest, one of the stages of the bone marrow transplant. The procedure is done blindly, performed without any visual feedback, except the external view of the donor body, and the physician needs to feel the skin and bone layers trespassed by the needle to find the bone marrow and then start the material aspiration. The simulator uses a robotic arm that operates with six degrees of freedom movements and provides force feedback to give to the user the tactile sensations felt during the penetration of the patient's body [11]. In the system, the robotic arm (Figure 1) simulates the needle used in the real procedure, and the virtual body visually represented has the tactile properties of the real tissues. The assessment tool proposed supervised the user movements during the puncture and evaluated the training according to M possible classes of performance.

ASSESSMENT TOOL BASED ON NAIVE BAYES

This section presents the method for training assessment, based on FNBayes. For reader's better understanding, we first present a short review about Naive Bayes method [20]. After that, we present the FNBayes method.

Naive Bayes Method

Formally, let be the classes of performance in space of decision $\Omega=\{1,...,M\}$ where M is the total number of classes of performance. Let be w_i, $i \in \Omega$ the class of performance for an user. A Naive Bayes classifier computes conditional class probabilities and then predict the most probable class of a vector of training data X, according to sample data D, where X is a vector with n features obtained when a training is performed, i.e. $X=\{X_1, X_2, \ldots, X_n\}$. Using the Bayes Theorem:

$$\begin{aligned} P(w_i \mid X) &= [P(X \mid w_i)\, P(w_i)] \,/\, P(X) \Leftrightarrow \\ \Leftrightarrow P(w_i \mid X_1, X_2, \ldots, X_n) &= \\ &= [P(X_1, X_2, \ldots, X_n \setminus w_i)\, P(w_i)] \,/\, P(X) \end{aligned} \tag{1}$$

However, as $P(X)$ is the same for all classes w_i, then it is not relevant for data classification and can be rewritten as:

$$P(X \mid w_i)\, P(w_i) = P(X_1, X_2, \ldots, X_n \setminus w_i)\, P(w_i) \tag{2}$$

The equation (2) is equivalent to the joint probability model:

$$P(X_1, X_2, \ldots, X_n \setminus w_i)\, P(w_i) = P(X_1, X_2, \ldots, X_n , w_i) \tag{3}$$

Now, using successive applications of the conditional probability definition over equation (3), can be obtained:

$$
\begin{aligned}
P(X_1, X_2, \dots, X_n, w_i) &= P(w_i)\, P(X_1, X_2, \dots, X_n \backslash w_i) \\
&= P(w_i)\, P(X_1 \backslash w_i)\, P(X_2, \dots, X_n \backslash w_i, X_1) \\
&= P(w_i)\, P(X_1 \backslash w_i)\, P(X_2 \backslash w_i, X_1)\, P(X_3, \dots, X_n \backslash w_i, X_1, X_2) \\
&\dots \\
&= P(w_i)\, P(X_1 \backslash w_i)\, P(X_2 \backslash w_i, X_1) \dots P(X_n \backslash w_i, X_1, X_2, \dots, X_{n-1})
\end{aligned}
$$

The Naive Bayes classifier receives this name because its naive assumption of each feature X_k is conditionally independent of every other feature X_l, for all $k \neq l \leq n$. It means that knowing the class is enough to determine the probability of a value X_k. This assumption simplifies the equation above, due to:

$$P(X_k \backslash w_i, X_l) = P(X_k \backslash w_i) \quad (4)$$

for each X_k and the equation (3) can be rewritten as:

$$
\begin{aligned}
P(X_1, X_2, \dots, X_n, w_i) &= \\
&= P(w_i)\, P(X_1 \backslash w_i)\, P(X_2 \backslash w_i) \dots P(X_n \backslash w_i) \quad (5)
\end{aligned}
$$

unless a scale factor S, which depends on $X_1, X_2, \dots, X_n$. Finally, equation (1) can be expressed by:

$$P(w_i \mid X_1, X_2, \dots, X_n) = (1/S)\, P(w_i)\, \Pi^{n}_{k=1} \; P(X_k \backslash w_i) \quad (6)$$

Then, the classification rule for Naive Bayes is done by:

$$
\begin{aligned}
&X \in w_i \text{ if } P(w_i \mid X_1, X_2, \dots, X_n) > P(w_j \mid X_1, X_2, \dots, X_n) \\
&\text{for all } i \neq j \text{ and } i, j \in \Omega \quad (7)
\end{aligned}
$$

and $P(w_* \mid X_1, X_2, \dots, X_n)$ with $* = \{i, j \mid i, j \in \Omega\}$, is done by (6).

To estimate parameters for $P(X_k \backslash w_i)$ for each class i, it was used a maximum likelihood estimator, named P_e:

$$P_e(X_k \backslash w_i) = \#(X_k, w_i) / \#(w_i) \quad (8)$$

where $\#(X_k, w_i)$ is the number of sample cases belonging to class w_i in all sample data D and having the value X_k, $\#(w_i)$ is the number of sample cases that belong to the class w_i in all sample data D.

FNBayes Method

Several authors proposed versions of Fuzzy Naive Bayes method. Tang et al. [30] proposed a Fuzzy Naive Bayes method with two stages: in the first one, a fuzzy clustering algorithm determines partitions in space of decision. In the second stage, the partitions obtained in the first stage are used to estimate the parameters for linguistic variables. With that methodology, it is possible to use continuous variables and to decrease the learning complexity of Naive Bayes method. In another paper, Tang et al. [31] analyses the model identification using weighted fuzzy production rules. After that, the accuracy of fuzzy production rules is investigated using genetic algorithms [32].

Other approaches were used for fuzzy models of Naive Bayes method. Borgelt [1] extended the Naive Bayes method to manipulate some kinds of fuzzy information. Nurnberger [25] made mappings from Naive Bayes method to a NEFCLASS modified algorithm to improve the first one. Borgelt [2] use Fuzzy Maximum Likelihood Estimation [6] to determine fuzzy partitions.

There is a third approach, in which fuzzy discretization methods [8,33] were used in the first stage to allow use Naive Bayes method after. However, this approach can affect classification bias and variance of Naive Bayes method.

Störr [29] proposed another approach which has some advantages: is fast; is able to work with few training examples; is able to deal with missing attributes; can be used for incremental learning and if all fuzzy membership functions assume values in {0;1}, that approach has the same behavior than Naive Bayesian classification algorithm.

Based on the same space of decision with M classes, the FNBayes method computes conditional class probabilities and then predict the most probable class of a vector of training data $X=\{X_1, X_2, \dots, X_n\}$, according to sample data D. In this case, it is assumed each X_k, $k=1,\dots,n$, is a linguistic variable and it is expressed by linguistic values, with normalized membership functions $\mu_i(X_k)$, where $i=1,\dots,M$. Those functions in FNBayes method are interpreted as conditional information of class w_i done by a variable X_k [29]. Then, let $X = \{ X_1 = A_{1i}, \dots, X_n = A_{ni} \}$ and using Bayes:

$$P(w_i \backslash X) = [P(X \backslash w_i)\, P(w_i)\, \mu_i(X)]/P(X) \quad (9)$$

As before, the Naive Bayes method assumes conditionally independent among the events in X. It modifies the equation (9) to:

$$P(w_i \backslash X) = (1/S)\, P(w_i)\, \Pi^{n}_{k=1} \; [P(X_k \backslash w_i)\, \mu_i(X)] \quad (10)$$

Then, the classification rule for FNBayes is done by:

$$
\begin{aligned}
&X \in w_i \text{ if: } P(w_i \backslash X) > P(w_j \backslash X), \\
&\text{for all } i \neq j \text{ and } i, j \in \Omega \quad (11)
\end{aligned}
$$

where $P(w_i \backslash X) = P(w_i \backslash X_1 = A_{1i}, \dots, X_n = A_{ni})$, is done by (10).

The Assessment Tool

The assessment tool proposed should supervise the user's movements and other parameters associated to them. The system must collect information about positions in the space, forces, torque, resistance, speeds, accelerations, temperatures, visualization position and/or visualization angle, sounds, smells and etc. The virtual reality simulator and the assessment tool are independent systems, however they act simultaneously. The user's interactions with the simulator are monitored and the information is sent to the assessment tool that analyzes the data and emits a report on the user's performance at the end of the training. Depending on the application, all those variables or some of them will be monitored (according to their relevance to the training).

The virtual reality system used for the tests is a bone marrow harvest simulator [11]. In a first movement on the real procedure, the trainee must feel the skin of the human pelvic area to find the best place to insert the needle used for the harvest. After, he must feel the tissue layers (epidermis, dermis, subcutaneous, periosteum and compact bone) trespassed by the needle and stop at the correct position to do the bone marrow extraction. In our VR simulator the trainee interacts with a robotic arm and his/her movements are monitored in the system by some variables [11]. For reasons of general performance of the VR simulator, were chosen to be monitored the following variables: spatial position, velocities, forces and time on each layer. Previously, the system was calibrated by an expert, according M classes of performance defined by him. The calibration process consists in to execute several times the procedure and to classify each one according to classes of performance. The number of classes of performance was defined as $M=3$: 1) correct procedures, 2) acceptable procedures, 3) badly executed procedures. So, the classes of performance for a trainee could be: "you are well qualified", "you need some training yet", "you need more training".

The information of variability about these procedures is acquired using FNBayes method. In our case, we assume that the font of information for w_i classes is the vector of the sample data D. The user makes his/her training in virtual reality simulator and the Assessment Tool based on FNBayes collects the data from his/her manipulation. All probabilities of that data, for each class of performance, are calculated by (10) and, at the end, the user is assigned to a w_i class of performance by (11). So, when a trainee uses the system, his performance is compared with each expert's class of performance and the Assessment Tool based on FNBayes assigns him the better class, according to the trainee's performance. At the end of training, the assessment system reports the classification to the trainee.

Conclusions and Future Works

In this paper we presented a new approach to online training assessment in virtual reality simulators. This approach uses an Assessment Tool based on FNBayes and solves the main problems in assessment procedures: use of continuous variables, low complexity and high accuracy. Systems based on this approach can be applied in virtual reality simulators for several areas and can be used to assess a trainee into classes of learning giving him a status about his performance.

As future work, we intend to test and to make a statistical comparison between others methodologies and the methodology proposed in this paper.

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