ASSESSMENT BASED ON NAIVE BAYES FOR TRAINING BASED ON VIRTUAL REALITY

Ronei Marcos de Moraes[1], Liliane dos Santos Machado [2]

Abstract *— Nowadays several areas present training systems based on virtual reality. In these systems the user is immersed into a virtual world to perform realistic training. However, it is important to know the quality of training to provide a status about the user performance. An online assessment system allows the user to improve his learning because it can identify, immediately after the training, where user made mistakes or presented low efficiency. Recently, several approaches have been proposed to perform on-line or off-line evaluation in training simulators based on virtual reality. In this work we present a new approach to on-line evaluation based on Naive Bayes Classifier for modeling and classification of simulation in pre-defined classes of training. Naive Bayes Classifiers are a special case of probabilistic networks or Bayesian Networks to compute conditional probabilities, over the data for each class of performance, and decide for the most probable.*

Index Terms — Naive Bayes, Assessment, Training based on Virtual Reality, Online Assessment System.

INTRODUCTION

Virtual Reality (VR) systems have been used for training of several procedures since the 2nd World War when the first flying simulators were developed [18]. Nowadays, several kinds of training are already executed in virtual reality simulators [2]. The goal of these systems is to provide a training environment similar to a real procedure environment by the use of devices and techniques that explore the human senses. In medicine, the use of virtual reality systems for training is beneficial in cases where a mistake could result in physical or emotional impact on patients. Systems for different modalities in medicine have been developed, as training in laparoscopy [22], prostate examination [1], ocular surgery [8] and bone marrow harvest [5]. These systems, as other VR based simulators for training, could be improved by the incorporation of assessment tools to allow evolution analyses of user performance. However, several kinds of training based on VR use to record the user actions in videotapes to post-analysis by experts [1]. In these cases, the user receives his assessment after some time. 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 on-line assessment tool incorporated into to a simulation system based on virtual reality is important to allow the learning improvement and users assessment.

Just a few years ago were proposed the first methodologies for training assessment. They can be divided in off-line and on-line methods. In medicine, some models for off-line [10, 18, 19] or on-line [4, 6, 12, 13, 14] assessment of training have been proposed. 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 on-line assessment tools due the fact that these methods allows the user to easily remember his mistakes and learn how to correct.

The main problems related to on-line training assessment methodologies applied to VR systems are computational complexity and accuracy. An on-line assessment tool must have low complexity to do not compromise VR simulations performance, but it must has high accuracy to do not compromise the user assessment. To verify those requirements, an assessment tool based on Naive Bayes was implemented in a bone marrow harvest simulator 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 [2, 21]. 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

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positioned provides 3D sound, and touch can be simulated by the use of haptic devices [7, 20].

Virtual reality systems for training can provide significant benefits over other methods of training, mainly in 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 [9] and these data can be used in an assessment [4, 18]. One kind of haptic device is based on a robotic arm (Figure 1) 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 [7]. 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.

FIGURE. 1
A haptic device used in VR systems.

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 [20]. 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 [1]. Recently, some models for off-line or on-line assessment of training have been proposed, some of them use Discrete Hidden Markov Models (DHMM) [18] or Continuous Hidden Markov Models (CHMM) [19] to modeling forces and torque during a simulated training in a porcine model. Machado et al. [4] 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. [10] acquired and compared postural and movement data of experts and residents in different contexts by use of distributions statistics. Machado and Moraes proposed the use of Maximum Likelihood [12], Fuzzy Gaussian Mixture Models [13], and recently Fuzzy Neural Networks [6] and Fuzzy Bayes Rule [15], among others. They also proposed a methodology to automatically assess a user's progress to improve his/her performance in virtual reality training systems [14] using statistical measures and models (time dependent or not) as well as a fuzzy expert system. After that, Morris et al. [16] suggest the use of statistical linear regression to evaluate user's progress in a bone surgery.

In this paper, we propose a new statistical system for assessment based on Naive Bayes classifier. This system can perform an on-line 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.

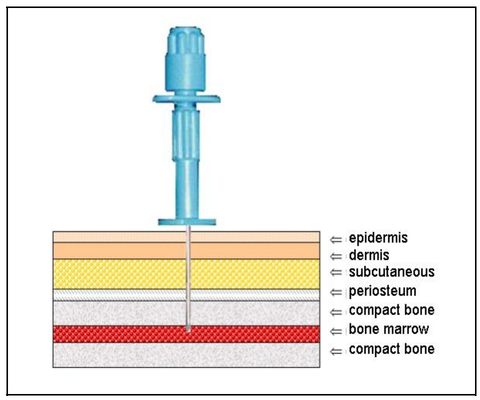

FIGURE. 2
The tissue layers trespassed by needle in a bone marrow harvest.

To test the method proposed, we are using a bone marrow harvest simulator [5]. 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 (Figure 2). 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 (Figure 3) [11]. In the system the robotic arm 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.

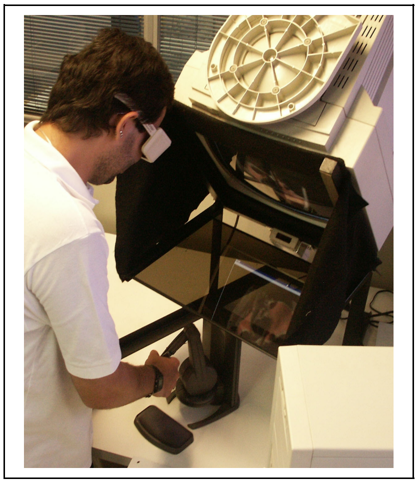

FIGURE 3
THE VIRTUAL REALITY BASED SIMULATOR FOR BONE MARROW HARVEST TRAINING IN USE.

ASSESSMENT TOOL BASED ON NAIVE BAYES

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

Classical Bayes Classifier

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. We can determine the most probable class of a vector of training data X by conditional probabilities [3]:

$$P(w_i \mid X)=P(w_i \cap X) \,/\, P(X), \text{ where } i\in\Omega. \tag{1}$$

The probability done by (1) gives the likelihood that for a data vector X, the correct class is w_i. Classification rule is performed according to

$$X \in w_i \text{ if } P(w_i \mid X) > P(w_j \mid X) \text{ for all } i \neq j, \text{ and } i, j \in\Omega. \tag{2}$$

However, all the probabilities done by (1) are unknown. Then, if we have sufficient information available for each class of performance, we can estimate that probabilities, denoted by $P(X \mid w_i)$. Using the Bayes Theorem:

$$P(w_i \mid X) = [P(X \mid w_i)\, P(w_i)] \,/\, P(X), \tag{3}$$

where $P(X) = \Sigma^{M}_{i=1}\ P(X \mid w_i)\, P(w_i)$.

As $P(X)$ is the same for all classes w_i, then it is not relevant for data classification. In Bayesian theory, $P(w_i)$ is called a priori probability for w_i and $P(w_i \mid X)$ is a posteriori probability for w_i where X is known. Then, the classification rule done by (2) is modified:

$$X \in w_i \text{ if } P(X \mid w_i)\, P(w_i) > P(X \mid w_j)\, P(w_j) \text{ for all } i \neq j \text{ and } i, j \in\Omega. \tag{4}$$

Equation (4) is known as Bayesian decision rule of classification. However, it can be convenient to use [4]:

$$\begin{aligned} g(X) &= \ln\, [P(X \mid w_i)\, P(w_i)] \\ &= \ln\, [P(X \mid w_i)] + \ln\, [P(w_i)], \text{ with } i \in\Omega. \end{aligned} \tag{5}$$

where $g(X)$ is known as discriminant function. We can use (5) to modify the formulation done by Bayesian decision rule in equation (4):

$$X \in w_i \text{ if } g_i\,(X) > g_j\,(X) \text{ for all } i \neq j \text{ and } i, j \in\Omega. \tag{6}$$

It is important to note that if statistical distribution of training data can assume multivariate Gaussian distribution, the use of (6) has interesting computational properties [3]. If training data cannot assume that distribution, the equation (6) can provides a significant reduction of computational cost of implementation.

Naive Bayes Classifier

Based on the same space of decision with M classes, a Naive Bayes classifier computes conditional class probabilities and then predict the most probable class of a vector of training data X, where X is a vector with n features obtained when a training is performed, i.e. $X=\{X_1, X_2, ..., X_n\}$. From equation (3):

$$\begin{aligned} &P(w_i \mid X) = [P(X \mid w_i)\, P(w_i)] \,/\, P(X) \Leftrightarrow \\ &\Leftrightarrow P(w_i \mid X_1, X_2, ..., X_n) = \\ &\quad = [P(X_1, X_2, ..., X_n \setminus w_i)\, P(w_i)] \,/\, P(X) \end{aligned} \tag{7}$$

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:

$$P(X \mid w_i)\, P(w_i) = P(X_1, X_2, ..., X_n \setminus w_i)\, P(w_i) \tag{8}$$

The equation (8) is equivalent to the joint probability model:

$$P(X_1, X_2, ..., X_n \setminus w_i)\, P(w_i) = P(X_1, X_2, ..., X_n\, , w_i) \tag{9}$$

Now, using successive applications of the conditional probability definition over equation (9), can be obtained:

$$\begin{aligned} &P(X_1, X_2, ..., X_n\, , w_i) = P(w_i)\, P(X_1, X_2, ..., X_n \setminus w_i) \\ &= P(w_i)\, P(X_1 \setminus w_i)\, P(X_2, ..., X_n \setminus w_i\, , X_1) \end{aligned}$$

$= P(w_i)\ P(X_1 \setminus w_i)\ P(X_2 \setminus w_i , X_1)\ P(X_3, \ldots, X_n \setminus w_i , X_1, X_2)$

$\ldots$

$= P(w_i)\ P(X_1 \setminus w_i)\ P(X_2 \setminus w_i , X_1) \ldots P(X_n \setminus w_i , X_1, X_2 ,\ldots,X_{n-1})$

The Naive Bayes classifier receive 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:

$$P(X_k \setminus w_i , X_l) = P(X_k \setminus w_i) \qquad (10)$$

for each X_k and the equation (9) can be rewritten as:

$$P(X_1, X_2, \ldots, X_n , w_i) = \\ = P(w_i)\ P(X_1 \setminus w_i)\ P(X_2 \setminus w_i) \ldots P(X_n \setminus w_i) \qquad (11)$$

unless a scale factor S, which depends on $X_1, X_2, \ldots, X_n$. Finally, equation (7) can be expressed by:

$$P(w_i \mid X_1, X_2, \ldots, X_n) = (1/S)\ P(w_i)\ \Pi^{n}{}_{k=1}\ \ P(X_k \setminus w_i) \qquad (12)$$

Then, the classification rule for Naive Bayes is similar those done by (4):

$$X \in w_i \text{ if } P(w_i \mid X_1, X_2, \ldots, X_n) > P(w_j \mid X_1, X_2, \ldots, X_n) \\ \text{for all } i \neq j \text{ and } i, j \in \Omega \qquad (13)$$

and $P(w_* \mid X_1, X_2, \ldots, X_n)$ with $* = \{i, j \mid i, j \in \Omega\}$, is done by (12).

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

$$P_e(X_k \setminus w_i) = \#(X_k , w_i) / \#(w_i) \qquad (14)$$

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

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 [5]. 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 [5]. 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 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 probability models. In our case, we assume that the font of information for w_i classes is the vector of the sample data. The user makes his/her training in virtual reality simulator and the Assessment Tool based on Naive Bayes collects the data from his/her manipulation. All probabilities of that data for each class of performance are calculated by (14) and at the end the user is assigned to a w_i class of performance by (13). So, when a trainee uses the system, his performance is compared with each expert's class of performance and the Assessment Tool based on Naive Bayes 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.

Before any training, the calibration of the assessment tool based on Naive Bayes was performed by an expert. For that, an expert executed the procedure twenty times for each class of performance. The necessary parameters for modeling each class are obtained and after that calibration, the system is ready for use.

Conclusions and Future Works

In this paper we presented a new approach to on-line training assessment in virtual reality simulators. This approach uses an Assessment Tool based on Naive Bayes and solves the main problems in assessment procedures: 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 classify a trainee into classes of learning giving him a status about his performance. The assessment system was implemented in a bone marrow harvest simulator based on virtual reality with success.

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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References

[1] Burdea, G., Patounakis, G., Popescu, V. and Weiss, R.E. "Virtual Reality Training for the Diagnosis of Prostate Cancer". *Virtual Reality Annual International Symposium Proceedings. IEEE*, 1998. pp. 190-197.

[2] Burdea, G. and Coiffet, P. *Virtual Reality Technology*. 2nd ed., Wiley Interscience, 2003.

[3] Johnson, R. A.; Wichern, D. W., *Applied Multivariate Statistical Analysis*. Prentice Hall, 4th ed., 1998.

[4] Machado, L. S., Moraes, R. M. and Zuffo, M. K. "Fuzzy Rule-Based Evaluation for a Haptic and Stereo Simulator for Bone Marrow Harvest for Transplant". 5th Phantom Users Group Workshop Proceedings, 2000.

[5] Machado, L. S., Mello, A. N., Lopes, R. D., Odone Fillho, V. and Zuffo, M. K. "A Virtual Reality Simulator for Bone Marrow Harvest for Pediatric Transplant". *Studies in Health Technology and Informatics*. Vol. 81. 2001, pp.293-297.

[6] Machado, L. S.; Moraes, R. M. "Online Training Evaluation in Virtual Reality Simulators Using Evolving Fuzzy Neural Networks". Proceedings of the *6th International FLINS Conference*. Belgium. 2004, pp.314-317.

[7] Mahoney, D.P. "The Power of Touch". *Computer Graphics World*. Vol. 20, No. 8. August, 1997, pp. 41-48.

[8] Mahoney, D.P. "The Eyes Have It". *Computer Graphics World*, Vol. 21, No. 8. August 1998, pp. 69-70.

[9] Massie, T., Salisbury, K. "The PHANToM Haptic interface: A device for probing virtual objects". *ASME Winter Annual Meeting*, DSC. Vol. 55, No 1. 1994, pp. 295-300.

[10] McBeth, P. B. et al. "Quantitative Methodology of Evaluating Surgeon Performance in Laparoscopic Surgery". *Studies in Health Technology and Informatics*. Vol. 85. 2002, pp. 280-286.

[11] Moody, L., Baber, C., Arvanitis, T. N. "Objective Surgical Performance Evaluation Based on Haptic Feedback". *Studies in Health Technology and Informatics*. Vol. 85. 2002, pp. 304-310.

[12] Moraes, R. M.; Machado, L. S. "Maximum Likelihood for On-line Evaluation of Training Based on Virtual Reality". Proceedings of Global Congress on Engineering and Technology Education (GCETE'2005). Março, Santos, Brasil. 2005, pp. 299-302.

[13] Moraes, R. M.; Machado, L. S. "Fuzzy Gaussian Mixture Models for On-line Training Evaluation in Virtual Reality Simulators". Annals of the *International* Conference on Fuzzy *Information Processing* (FIP'2003). March, Beijing, Vol. 2. 2003, pp. 733-740.

[14] Moraes, R. M.; Machado, L. S.; Continuous Evaluation in Training Systems Based on Virtual Reality. Proceedings of *Global Congress on Engineering and Technology Education* (GCETE'2005). March, Santos, pp.1048-1051.

[15] Moraes, R. M.; Machado, L. S. "On-line Training Evaluation in Virtual Reality Simulators using Fuzzy Bayes Rule". Proceedings of the *7th International FLINS Conference on Applied Artificial Intelligence* (FLINS'2006). August, Genova, 2006, pp. 791-798.

[16] Morris, D.; Sewell, C.; Barbagli, F. et all; Visuohaptic simulation of bone surgery for training and evaluation. *IEEE Computer Graphics and Applications*, v.26 n. 6, 2006, pp. 48-57.

[17] Pimentel, K.., Teixeira, K. *Virtual Reality – Through the New* Looking Glass. 2nd ed, McGraw Hill, 1995.

[18] Rosen J., Richards, C., Hannaford, B. and Sinanan, M. "Hidden Markov Models of Minimally Invasive Surgery". *Studies in Health Technology and Informatics*. Vol. 70. 2000, pp. 279-285.

[19] Rosen, J., Solazzo, M., Hannaford, B. and Sinanan, M. "Objective Laparoscopic Skills Assessments of Surgical Residents Using Hidden Markov Models Based on Haptic Information and Tool/Tissue Interactions". *Studies in Health Technology and Informatics*. Vol. 81. 2001, pp. 417-423.

[20] Salisbury, K. "Haptics: The Technology of Touch". *HPCWire Special*. No 10. Nov 1995.

[21] Vince, J. *Virtual Reality Systems*. Addison-Wesley, 1995.

[22] Voss, G.; Brockholt, U.; Los Arcos, J.; Müller, W.; Oppelt, P.; Stäler, J. L. "Intelligent Training System for Laparoscopy and Hysteroscopy". *Studies in Health Technology and Informatics*. No 70. 2000, pp. 359-364.