A NEW APPROACH FOR ONLINE TRAINING ASSESSMENT FOR BONE MARROW HARVEST WHEN PATIENTS HAVE BONES DETERIORATED BY DISEASE

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Abstract — *Training systems based on virtual reality have been used in several areas. In these systems users are immersed into a virtual world to have realistic training through realistic interactions. In such systems, as in any other training form, is important to know the quality of user's training. Several approaches to perform assessment in training simulators based on virtual reality have been proposed. However they did not present a satisfactory solution for special cases, as a bone marrow harvest in patients with bones deteriorated by disease. In this paper, we present a new approach to online training assessment based on Modified Naive Bayes, which can manipulate qualitative and quantitative variables simultaneously. A comparison with an assessment system based on Naive Bayes was performed and showed the new method is more accurate and faster.*

Index Terms — *Training based on Virtual Reality, Users' Assessment, Medical Simulation, Pattern Recognition.*

INTRODUCTION

Training systems based on virtual reality (VR) have been used in several areas [2]. In such systems, immersive and interactive virtual environments are used to allow users to perform tasks that simulate real situations, in the same way the user will experiment in reality. It is interesting to monitor users' interactions in order to know the quality of users' skills to perform that task. Thus, it is necessary to develop methodologies to assess users' training.

Several kinds of training based on VR use to record users actions in videotapes for post-analysis by experts. 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 online assessment tool incorporated into a simulation system based on virtual reality is important to allow the learning improvement and users assessment [6] since it can provide a quick feedback about the user's performance. It is also important the fact that online methods provide fast (real-time) reports, what allows the user remember more easily his mistakes and learn how to correct them. As VR simulators are real-time systems, the online assessment tool must continuously monitor all user interactions and compare his performance with pre-defined expert's classes of performance.

In medicine, some models for assessment of training have been proposed [4,5,6,8,9,10,11]. Due to didactic reasons it is desirable an online assessment, which can produce an assessment immediately after the training [9]. The main challenges 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. Another inconvenient about those methods is related to an unsatisfactory solution for specific cases as in some medical procedures, where there are quantitative and qualitative information available to perform an assessment. It was not found an assessment method compatible with these restrictions in the literature.

Some of the models previously mentioned are based on Naive Bayes (NB) or some modification of that [10,12]. In such approaches models are applied for online assessment and use variables of a single type: qualitative or quantitative. However, online assessment in simulators of some special medical cases needs to analyze qualitative and quantitative information simultaneously to improve the decision quality. In this paper, we propose a Modified NB to lead with qualitative and quantitative variables simultaneously and also to assist the other requirements of an assessment system for training based on VR.

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]. More than a technology, VR became a new science that joins several fields as computers, robotics, graphics, engineering and cognition. VR worlds are 3D environments, created by computer graphics techniques, where one or more users are

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immersed totally or partially to interact with virtual elements. The realism of a VR application is given by the graphics resolution and by the exploration of users senses. Mainly, special devices stimulate the sight, hearing and touch. As example, head-mounted displays (HMD) or even ordinary monitors combined with special glasses can provide stereoscopic visualization; multiple sound sources positioned can provide 3D sound; and touch can be simulated by the use of haptic devices [2].

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 performed without any kind of visualization and the only information received is noticed by the touch sense provided by robotic devices with force feedback. These haptic devices can measure forces and torque applied during the user interaction and these data can be used in an assessment [6].

This way, user can feel objects texture, density, elasticity and consistency. Since the objects have physical properties, the user can identify them in a 3D scene (without see them) by the use of this kind of device [2]. This is especially interesting in medical applications to simulate proceedings in which visual information is not available. Particularly, some haptic devices have shape and hilt similar to medical tools and can be used to simulate surgical tools.

The bone marrow harvest simulator [7] has as goal the training of new doctors to execute a bone marrow harvest, one of the stages of the bone marrow transplant. The procedure is performed without any visual feedback except the external view of the patient body, and the physician needs to feel the skin and other tissue layers trespassed by the needle to find the bone marrow and then start the material aspiration.

The simulator uses a haptic device that operates with six degrees of freedom movements and provides force feedback to give to the user the tactile sensations felt during the puncture of the patient's body. In this simulator, 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.

In a traditional bone marrow harvest for transplant, multiple punctures are required (up to 20 per patient) in order to obtain enough bone marrow for the transplant. It requires specific applied force to penetrate the bone (to reach the marrow) without overstep it. However, some special situations can occur and demand specific skills of physician: the repetitive procedure can cause loss of control or fatigue of physician.

Another problem is the proximity between a first penetration and the next (generally about a centimeter), which requires sufficient dexterity of the operator. The properties of the bone region can change after each harvest, due to the penetrations. Additionally, in pediatric oncology is easy to find children with soft bone structures or bones with deterioration caused by disease which demands more attention and dexterity in the harvest procedure.

TRAINING ASSESSMENT

An assessment tool must supervise user movements during the training and assess the training according to M possible classes of performance. The assessment of trainee intends 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 [2]. Then, virtual reality systems can use one or more variables, as the mentioned above, to assess a simulation performed by user.

As mentioned before, several assessment methods have been proposed [6,9,10,11,13], where some of them, were proposed for traditional bone marrow harvest simulator. In that case, always was simulated the normal case, in which the bones are healthy. In the normal situations, several models found in the literature are be able to perform the online assessment successfully and all of them use variables of a single type: quantitative.

However, with relative frequency, the donor is the own patient. So, the main properties of the bones can present deterioration caused by disease. To model those cases, it is necessary to include some qualitative variables to lead with some properties of bones and the results of medical interactions with them, after each harvest. In the next Section, are provided details about the new methodology, called Modified Naive Bayes, to solve assessment problems in those are presented special cases of bone marrow harvest procedure.

MODIFIED NAIVE BAYES

This section presents theoretical aspects of the new method for training assessment. For reader's better understanding, we first present a short review about the classical Naive Bayes and in the following, we present the Modified Naive Bayes. An assessment method based on classical Naive Bayes was proposed by the authors in the past [10].

The Naive Bayes (NB) method must be applied over discrete or multinomial variables [1,10]. 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 NB method computes conditional class probabilities and then predict the most probable class of a vector of training data $\boldsymbol{X}$, according to sample data D, where $\boldsymbol{X}$ is a vector with n features obtained when a training is performed, i.e. $\boldsymbol{X}=\{X_1, X_2, ..., X_n\}$. Using the Bayes Theorem:

$$\begin{aligned} P(w_i \mid \boldsymbol{X}) &= [P(\boldsymbol{X} \mid w_i)\, P(w_i)] \,/\, P(\boldsymbol{X}) \Leftrightarrow \\ \Leftrightarrow \quad P(w_i \mid X_1, X_2, ..., X_n) &= \\ = [P(X_1, X_2, ..., X_n \backslash w_i)\, P(w_i)] \,/\, P(\boldsymbol{X}) & \end{aligned} \quad (1)$$

However, as $P(\boldsymbol{X})$ is the same for all classes w_i, then it is not relevant for data classification. The NB method receives this name because its naive assumption of each feature X_k is conditionally independent of every other feature X_l , for all k $\neq l \leq n$. Unless a scale factor S, which depends on $X_1, X_2, \ldots, X_n$, the equation (1) can be expressed by:

$$P(w_i \mid X_1, X_2, \ldots, X_n) = (1/S)\, P(w_i)\, \Pi^{n}_{k=1}\ P(X_k \setminus w_i) \quad (2)$$

Then, the assessment rule for NB is done by:

$$X \in w_i \ \ if\ \ P(w_i \mid X_1, X_2, \ldots, X_n) > P(w_j \mid X_1, X_2, \ldots, X_n)$$
$$for\ all\ i \neq j\ and\ i, j \in \Omega \quad (3)$$

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

$$P_e\,(X_k \setminus w_i)] = \#(X_k \setminus w_i) \,/\, \#\,(w_i) \quad (4)$$

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*.

As mentioned above, the NB method must be applied over discrete or multinomial variables. Some approaches were developed to use NB Method with continuous variables, as several discretization methods [1,14] were used in the first stage to allow the use of the Naive Bayes method after. However, this approach can affect classification bias and variance of the NB method [14]. Other approach is use quantitative and qualitative variables simultaneously [1] and to compute its parameters from *D*. Formally, let be $X_{cat}=\{X_1, X_2, \ldots, X_c\}$, *c* $(0 \leq c \leq n)$ categorical or discrete variables obtained from training data, as in classical Naive Bayes and $X_{cont}=\{X_{c+1}, X_{c+2}, \ldots, X_n\}$, *n-c* continuous variables, obtained from training data too. Thus, *X* is a vector with *n* features, with $X=X_{cat} \cup X_{cont}$. Now, the equation (2) can be rewritten as [1]:

$$P(w_i \mid X_1, X_2, \ldots, X_n) =$$
$$(1/S)\, P(w_i)\, \Pi^{c}_{k=1}\ P(X_k \setminus w_i) \times \Pi^{n}_{k=c+1}\ P(X_k \setminus w_i) \quad (5)$$

The equation (5) defines the Modified Naive Bayes (MNB) method for two distinct models of probability. For example, categorical variables can be modeled by multinomial distributions and discrete variables can be modeled by count of events in sample data *D* or by a discrete statistical probability distributions. The continuous variables can be modeled by probability density functions. All these distributions models can be adjusted and verified by statistical tests over the data. In the case of Gaussian distribution can be verified for all variables, the MNB can be reduced to Gaussian Naive Bayes [12]. Without lose of generality, the equation (5) can allow any combination of statistical distributions of probability.

Based on the same space of decision with *M* classes, a MNB method computes conditional class probabilities and then predicts the most probable class of a vector of training data *X*, according to sample data *D*. The parameters of MNB method are learning from data using the equation (4). The final decision about vector of training data *X* is done by equation (3), where $P(w_* \mid X_1, X_2, \ldots, X_n)$ *with* $* = \{i, j \mid i, j \in \Omega\}$, is done by (5).

THE ASSESSMENT TOOL BASED ON MNB

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. In spite of acting simultaneously the systems work in an independent way. 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 [7]. A special medical case was simulated: a child with soft bone structures. In a first movement 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. As in this case the child has soft bone structures, the trainee must execute that step of procedure carefully to avoid damage to child. The simulator uses categorical variables as flags to identify the damage regions of bone.

In VR simulator the trainee interacts with a robotic arm and his/her movements are monitored in the system by some variables [7]. For reasons of general performance of the VR simulator, were chosen the following variables to be monitored: 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 on execute several times the procedure and 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 was acquired using Modified Naive Bayes method. In this case, it was assumed that the font of information for w_i classes is the vector of the sample data *D*. The trainee makes his/her training in virtual reality simulator and the

Assessment Tool based on MNB collects the data from his/her manipulation. So, when a trainee uses the system, his/her performance is compared with each expert's class of performance and the Assessment Tool based on MNB assigns the better class, according to the trainee's performance. At the end of the training, the assessment system reports the classification to the trainee.

In this case, an approach for continuous data using Gaussian distribution was verified. The information about soft bone structures was codified as binary variable. To perform a realistic simulation, some specific areas of bone were considered soft and other were not. The results can be observed in the classification matrix at Table 1, in which can be observed that the assessment tool made mistakes in 20 cases.

TABLE I

CLASSIFICATION MATRIX FOR ASSESSMENT TOOL BASED ON MODIFIED NAIVE BAYES.

Class of performance according to expert	Class of performance according to Assessment Tool based on Modified Naive Bayes		
	1	2	3
1	45	5	0
2	8	36	6
3	1	0	49

To measure concordance between experts and the assessment tool, was used the Kappa coefficient. This coefficient has been used used with success to measure concordances between experts and between classifications algorithms in image processing [3]. This coefficient uses a classification matrix, as that one of Table I. The result obtained was Kappa coefficient K=80.0% with variance 1.7×10^{-3}. The average of CPU time consumed for evaluation of training based on Modified Naive Bayes was lower than one millisecond of CPU using a Centrino 1.86GHz PC compatible, with 1.5 GB of RAM and 80GB hard disk.

COMPARISON WITH AN ASSESSMENT TOOL BASED ON NAIVE BAYES

A comparison was performed between the Assessment Tool Based on Modified Naive Bayes (MNB) and the Assessment Tool based on Naive Bayes (NB) [10]. The NB was configured and calibrated by the expert for the same three classes used before. The same sixty samples of training (twenty of each class of performance) were used for calibration of the two assessment systems. Equally, the data of the same 150 procedures from users training were used for a controlled and impartial comparison between the two assessment systems.

The classification matrix obtained for NB is presented in the Table II. The Kappa coefficient was K=66.0% with variance 2.7×10^{-3}. In 34 cases, the assessment tool made mistakes. This performance is significant lower than MNB, in statistical terms. A possible cause for that is the conversion of continuous variables attributes to discrete variables and by consequence, there is a loss of information. About computational performance of the Assessment Tools, the one based on MNB was faster than the one based on NB too. The average of CPU time consumed for assessment of training based on NB was 0.2030 seconds of CPU using the same Centrino PC compatible.

TABLE II

CLASSIFICATION MATRIX FOR ASSESSMENT TOOL BASED ON NAIVE BAYES.

Class of performance according to expert	Class of performance according to Assessment Tool based on Naive Bayes		
	1	2	3
1	36	1	13
2	0	41	9
3	9	2	39

CONCLUSIONS

In this paper was presented an approach for online training assessment based on Modified Naive Bayes (MNB). This approach solves the main problems in assessment procedures: use of categorical, discrete and continuous variables simultaneously, low complexity and high accuracy. This methodology uses a vector of information, with data collected from user interactions and positions with the virtual reality simulator. These data are compared by the assessment system with M pre-defined classes of performance. A bone marrow harvest simulator was used to test the method proposed.

A special medical case was simulated in a bone marrow harvest simulator: a child with soft bone structures. The MNB demonstrated to be appropriate to assess this situation (according to Kappa coefficient), using categorical variables to monitor the damage region of bone. When compared with an Assessment Tool based on Naive Bayes (NB), the MNB was more accurate and faster.

Similar procedure can be used to monitor others special cases as mentioned in this paper. Systems based on this approach can be applied in virtual reality simulators for other areas due to its performance with real-time response.

ACKNOWLEDGMENT

This work is partially supported by Brazilian Council for Scientific and Technological Development, CNPq (Processes 310339/2009-0, 312375/2009-3 and 573710/2008-2).

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