ASSESSMENT OF COLLABORATIVE MEDICAL TRAINING BASED ON VIRTUAL REALITY USING POSSIBILISTIC NETWORKS

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

Abstract *— In medicine, there are procedures performed not by only one person, but by a team of professionals acting simultaneously. By the use of Virtual Reality (VR) is possible to create virtual rooms that join people to simulate medical procedures. In these cases, collaborative features are used to coordinate the interactions of the multiple participants in the environment. Thus, interactions and graphics representations must be processed in real time to provide a sense of realism for all participants. Due to the fact in some medical procedures the positioning of participants in the room is important, tracking devices can be used to capture each user position to allow knowing all users position in the room. To verify if the group performed the procedure correctly, is proposed the use of an assessment methodology based on possibilistic networks. The goal is allow training of teams, developing individual competences to work together.*

Index Terms — Collaborative Medical Training, Users' Assessment, Virtual Reality, Possibilistic Networks.

INTRODUCTION

Training systems based on Virtual Reality (VR) for simultaneous use in complex training environments are being planned [5], as virtual surgery rooms for several purposes of training. In the medical area was showed also that surgeons trained in VR systems could obtain better results [10] when compared to others trained by traditional methods. Additionally, the assessment of psychomotor skills in VR systems that include haptic devices can quantify surgical dexterity with objective metrics [7]. Due to those reasons, McCloy and Stone [18] pointed out the assessment of psychomotor skills as the future of medical teaching and training. It is possible that VR simulators can be used to provide metrics to a proficiency criterion in medicine as it is used in aviation nowadays [23].

The advances of computer systems are be able to provide training system for multiple users simultaneously at a low cost. Other important advance is the speed of input/output devices for virtual reality systems such as haptic devices [17]. Nowadays, it is possible to connect more than one interaction device on a single computer or can get them to communicate by a network. In several applications, it is important also to know individual users' positions. As two bodies cannot be in same place in reality, then two users can not be in same place in a virtual reality training simulation. Particularly in medicine, those occurrences may endanger the life of a patient.

Although the possibilities of training which can be simulated in VR systems, any kind of training has little value if the trainee does not have any feedback about his/her performance. Then, the existence of an assessment tool attached to a simulation system based on VR is important to allow the learning improvement and the users assessment. Some systems can provide methodologies to assess of users' performance [1, 11, 23]. In spite of those methodologies, they are concerned with the assessment of only one user at a time. Up to the time being, only one methodology which monitor multiple users in complex training environments based on virtual reality have been found in literature [17]. Thus, the main goal of this paper is to present a new approach for multiple users' assessment system in collaborative training environments based on Possibilistic Networks.

SINGLE USER'S ASSESSMENT SYSTEM (SUAS) IN VR SIMULATORS

The first methodologies for SUAS were proposed recently. The early works in that area probably were proposed by Dinsmore et al. [8,9,13] that used a quiz to assess users of a VR environment to identify subcutaneous tumors. Since those papers, mainly in medicine, several assessment methods were proposed [15,19,20,21,22,28]. A SUAS must continuously monitor all user interactions and compare his performance with pre-defined expert's classes of performance to recognize user’s level of training. Basically, SUAS can be divided in off-line and on-line. Off-line SUAS can be defined as methods not coupled to VR systems, whose assessment results are provided some time (which can be minutes, hours or days) after the end of the VR-based training. On the other hand, on-line SUAS are coupled to the training system and collect user data to provide a result of his/her performance at the end of the simulation [17].

An on-line SUAS works coupled to a VR simulator, as showed in the Figure 1 [20]. A SUAS should be capable to monitor user's interactions with the VR simulator by

[1] Ronei Marcos de Moraes, Department of Statistics, Federal University of Paraíba - CCEN, Cidade Universitária s/n, João Pessoa – PB, Brazil, ronei@de.ufpb.br
[2] Liliane dos Santos Machado, Department of Computer Science, Federal University of Paraíba - CCEN, Cidade Universitária s/n, João Pessoa – PB, Brazil, liliane@di.ufpb.br

variables such as Position (of user and of instruments used in the VR simulation), touch force and resistance, user's angle of visualization, sound, smell, sense of temperature, velocity and acceleration of interactions and felt shapes. All the information is sent to the SUAS which analyzes the data and emits, at the end of the training, an assessment report about the user's performance according pre-defined classes of performance. An on-line SUAS must have low complexity to do not compromise VR simulations performance, but it must have high accuracy to do not compromise the assessment.

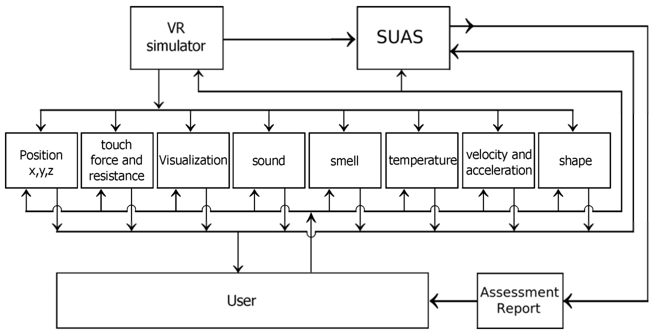

FIGURE. 1
DIAGRAM OF A VR SIMULATOR WITH A SUAS. ADAPTED FROM [13].

COLLABORATIVE TRAINING BASED ON VR

Virtual Environments (VE) have been used in educational context in several areas of knowledge [33], including medicine [27]. In general, these environments are designed to allow the acquisition of specific knowledge through the use of computer applications. Educational VEs can be explored to develop an environment that allows the presence of multiple users. Therefore, it is necessary to use techniques to join people in a common environment [30].

The concept of collaboration has several definitions in literature. In this work, collaboration is considered as the exchange of information by user interaction in a shared environment, i.e., collaboration happens when two or more users are included in a shared space performing a task together.

The use of collaborative VE make possible to replicate simulations in which participants can work together to achieve a common goal. In this context, they can be able to learn at the same time they contribute for others learning. The use of such environments in medical context can provide benefits to many professionals and students. For example, collaborative simulations can be used to overcome distance and provide remote monitored training in regions without experts. In this case, an expert physician can perform techniques through interactions in the VE and users can experience and follow his movements. Furthermore, collaboration in VR environments also enables a person to be part of a simulated training session with others, promoting the exchange of knowledge.

There are several approaches to achieve collaboration and those can be based on blocking and combination of movements. In the first case, only one person can manipulate the system and others can follow his movements or just visualize them. By the other hand, the combination of interactions can allow the composition of actions from all participants of the simulation and they can work together to achieve a common goal.

MULTIPLE USERS' ASSESSMENT SYSTEM (MUAS) IN VR SIMULATORS

As mentioned by [22], computational systems for multiple users have been developed since the 1990's: RB2 [3], DIVE [6], MR Toolkit [29]. Collaborative systems to provide interaction among multiple-user have been proposed too [2,14,24,32]. The main differences of training systems based on virtual reality for multiple users are: increase of complexity of the virtual reality system – use of clusters of computers or a computer capable to generate realistic multiple views, support changes in virtual environments for multiple users and support assessment system; high speed peer-to-peer network for communication among computers without compromising the simulation. Eventually, more than one haptic device were installed in a computer and/or tracking systems for each user in training.

Networks latency is the most common problem in distributed systems (based on network or Web) for multi-user interactions [26]. As consequences of this, users may have different views in the shared workspace which damages the users' performance involved in the simulation. A different approach for the assessment system is required for multi-user training [17]: to monitor all users in training according to relevant variables to the training; some tasks must be completed by specific users and according to a specific schedule; to take measures of specific interactions among users during the time of simulation and the time difference between them; to create a user profile and a group profile; to present low complexity not to compromise VR simulations performance, but present high accuracy level.

After extensive literature research, only one MUAS has been found: Moraes and Machado [17] proposed a MUAS based on fuzzy logic. The methodology proposed uses data collected from user interactions and group interactions during training. From that information, it is created user's and group profiles based on statistical tools and a time-dependent expert system based on fuzzy rules. Statistical tools are programmed to make an automatic analysis of the database and the fuzzy expert system uses those analysis to recognize patterns stored in the system for each user and for group. All rules are acquired from specialists knowledge in that medical procedure. At the end, two kinds of reports are created: an individual user and a group profiles. These assessment reports present individual and group profiles and shows the performance of specific tasks using statistics and some phrases in pseudo-natural language.

This way, a set of fuzzy rules of an expert system time dependent defines each one of the possible performance classes. This set is designed, for single users and for group, from experts´ knowledge. Additionally, interaction variables will be monitored according to their relevance to the training. Then, each application will have their own set of relevant variables which will be monitored [20]. The same happens with relevant variables which measure interactions among users in the group.

POSSIBILISTIC NETWORKS

This section presents the method for training evaluation, based on Possibilistic Networks. For reader's better understanding, we first present a short review about Bayes networks. After that, we present the Possibilistic Networks.

Bayesian Networks

A Bayesian network is a probabilistic model, which can represent a set of probabilities distributions from all variables in a complex process and also establish their relationships [25]. Formally, a Bayesian network is defined as directed acyclic graphs, denoted by G and a joint probability distribution denoted by P. The graph $G=(X,L)$ is a set of nodes and oriented arcs L, where nodes represent variables X in process and oriented arcs encode conditional dependencies between that variables [25]. The dependencies are modeled by specific conditional probabilistic distributions [12] for an attribute given the parent attributes in the network.

Formally, let be the classes of performance in space of decision $\Omega=\{1,\ldots,M\}$ where M is the total number of classes of performance. Let be w_i, $i \in \Omega$ the class of performance for an user. Let be a probability distribution P, which represents the joint domain of a set of n attributes $X=\{X_1, X_2, \ldots, X_n\}$, obtained when a training is performed. Thus:

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

It is possible simplify this methodology making the assumption that features are statistically independents. This assumption is called Naive Bayes and it simplifies the equation above, which can be rewritten as:

$$\begin{aligned} &P(X_1, X_2, \ldots, X_n, w_i) = \\ &= P(w_i)\, P(X_1 \backslash w_i)\, P(X_2 \backslash w_i) \ldots P(X_n \backslash w_i) \end{aligned} \tag{2}$$

unless a scale factor S, which depends on $X_1, X_2, \ldots, X_n$, from the equation (2):

$$\begin{aligned} &P(X_1, X_2, \ldots, X_n, w_i) = \\ &= (1/S)\, P(w_i)\, \Pi^n{}_{k=1}\; P(X_k \backslash w_i) \end{aligned} \tag{3}$$

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

$$\begin{aligned} X \in w_i \;\; if \;\; &P(w_i)\, \Pi^n{}_{k=1}\; P(X_k \backslash w_i) > \\ &P(w_j)\, \Pi^n{}_{k=1}\; P(X_k \backslash w_j) \text{ for all } i \neq j \end{aligned} \tag{4}$$

Possibilistic Networks

Formally, a Possibilistic Network is defined by (Y,L,π), where Y is a set of nodes, L are oriented arcs, and π is a possibility distribution. As in Bayesian Networks, the possibility distribution π represents the joint domain of a set of n attributes $X=\{X_1, X_2, \ldots, X_n\}$, obtained when a training is performed . According to Borgelt and Gebhardt [4] and due to the symmetry in the definition of conditional possibility distribution:

$$\pi(w_i \backslash X_1, X_2, \ldots, X_n) = \pi(X_1, X_2, \ldots, X_n \backslash w_i) \tag{5}$$

It is possible simplify this methodology making the assumption that features do not have any possibilistic interactions. This assumption is similar to the statistical independency. Besides, as the possibilistic approach is simpler than Bayes rule, and it is not necessary take account of a normalization constant or of prior class probabilities. This approach is called Naive Bayes Style Possibilistic Network by [4]. So, the equation (5) can be rewritten as:

$$\begin{aligned} &\pi(w_i \backslash X_1, X_2, \ldots, X_n) = \\ &= min\, \{\pi(X_1 \backslash w_i), \pi(X_2 \backslash w_i), \ldots, \pi(X_n \backslash w_i)\} \\ &= min_N\, \{\pi(X_1 \backslash w_i)\}, \text{ where } N=1,\ldots,n. \end{aligned} \tag{6}$$

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

$$\begin{aligned} X \in w_i \quad if\!: \;\; &min_N\, \{\pi(X_1 \backslash w_i)\} > min_N\, \{\pi(X_1 \backslash w_j)\} \\ &\text{for all } i \neq j \text{ and } i, j \in \Omega \end{aligned} \tag{7}$$

A NEW MUAS BASED ON POSSIBILISTIC NETWORKS

A MUAS must be interconnected with all users and must receive from them synchronized information about all variables of interest. A MUAS works coupled to a virtual reality simulator, as showed in the Figure 1 and it should be capable to monitor individual user's interactions and simultaneously, the interactions among users. In order to reach that, it is necessary to collect information about user's position in the space using tracking systems [31]. User's in the simulation should respect the physics laws and to train their proper positions in the procedure. About users' interactions is necessary data from forces, torque, resistance, speeds, accelerations, temperatures, visualization and/or visualization angle, sounds, smells, etc. To collect some information as force, force feedback, angles and torques, it is necessary to use specific devices to provide them. This information will be collected for each user in training system, as well as for all groups, to be used to feed the MUAS. Additionally, synchronization in time and space is necessary for all users to measure interactions among them, to determine the ordering of tasks and to provide details of user's performance [17]. Then, each application will have their own set of relevant variables which will be monitored for each user and also another set of relevant variables which measure interactions among users in the group.

All those information is used by MUAS, which analyses the data and emits, at the end of the training, an assessment report about the individual user's performance according pre-defined classes of performance, as well as, another assessment report about the group performance. Statistical tools are programmed to make an automatic analysis of the database and construct statistical measures, hypothesis testing and time dependent statistical models. From those statistical information, specialized Possibilistic Networks create individual user and group profiles and reports. Figure 2 shows a specialized Possibilistic Network to assess user's performance.

It is important to note that the Possibilistic Network which is a kernel of this assessment system is different of that one which is a kernel of a SUAS proposed by [22]. That Possibilist Network used just data collected from user's interactions without any processing and that one could not be applied in the case of the present paper.

Figure 3 shows the new methodology presented. The Individual Assessment System is based on a specialized Possibilistic Network as that one presented in the Figure 2. To construct MUAS, the Group Assessment Tool, the Users and Group Profiles were also added. Both of them are based on specialized Possibilistic Networks which analyse data from specialized tasks. In the first one assess all tasks which the group should perform and the second one assess users' interactions should perform among them. The N users perform their training using a VR Simulator and interacting with a Interactive System, which is responsible by management of the VR simulator. The Interactive System must provide visual and haptic simulations for all users according their point of view and their haptic devices. From these information, statistical measures, models and hypothesis testing are calculated and they are used as input for specialized Possibilistic Networks, which analyze that information to recognize individual user’s and group levels of training.

At the end of training, the new MUAS creates two kinds of report: individual assessment report, for each user, and the group assessment report. The first report is about the individual user performance on the training and the second assessment report is about group performance and the interactions among users during training. Those kinds of interactions are monitored to correct and improve details in specific procedures, as sequential tasks, simultaneous tasks or collaborative tasks. These kinds of tasks are common in surgical rooms and the group's performance in some tasks can be essentials for the life and the patient's recovery.

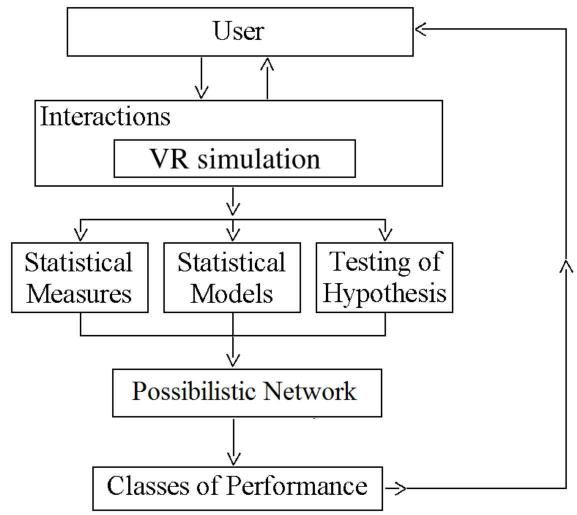

FIGURE. 2
A SPECIALIZED POSSIBILISTIC NETWORK.

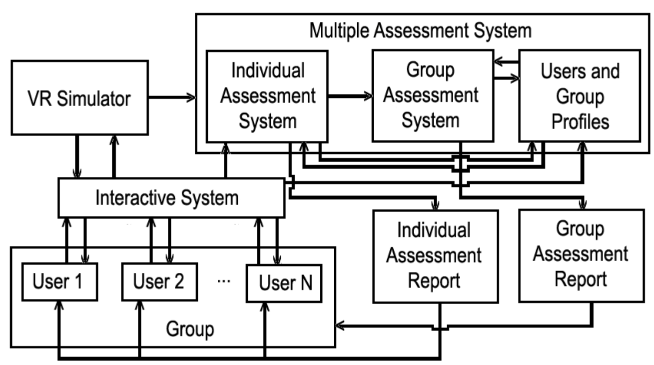

FIGURE. 3
DIAGRAM OF NEW MUAS. ADAPTED FROM [17]

The methodology proposed here for MUAS can be used for several kind of training in medicine, as procedures in surgical rooms, training paramedics groups in emergency situations, etc. As it is a generic methodology and can be used in training systems for other areas too. As the MUAS proposed by [22], there is no classification for this MUAS as on-line or off-line, because MUAS are not be able to generate reports immediately after of the end of training session.

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