Gaussian Mixture Models and Relaxation Labeling for Online Evaluation of Training in Virtual Reality Simulators

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

Abstract — *Several approaches for evaluation of online or offline training in simulators based on virtual reality have been proposed. However great part of these approaches has a high complexity and it demands large computational structure, what is very expensive. An online evaluator must have low complexity algorithm to do not compromise the performance of simulator. We propose a new approach to online evaluation of training in simulators based on virtual reality. This approach uses Gaussian Mixture Models and Relaxation Labeling (GMM-RL) for modeling and classification of the simulation in pre-defined classes of training. This method provides the use of continuous variables without lost of information. So, it solves the problem of low complexity in online evaluators without compromise performance of the simulator and with good evaluation accuracy. Systems based on this approach can be applied in virtual reality simulators for training in several areas.*

Index Terms — *Gaussian Mixture Models, Relaxation Labeling, Training Evaluation, Virtual Reality.*

INTRODUCTION

The existence of an online evaluation tool in simulation system based on virtual reality is important to allow the learning improvement and users evaluation. Recently, new methods of evaluation for online training in virtual reality simulator have been proposed [5, 7, 11, 13, 14, 18, 19].

In medicine, some models for offline or online evaluation of training have been proposed. However, great part of these approaches depends of large computational structure, which is very expensive to be available in some Medical Centers in Brazil and several other countries.

Simulators bases on virtual reality (VR) for training need high-end computers to provide realistic haptics, stereoscopic visualization of 3D models and textures. Online evaluators must have low complexity to do not compromise performance of simulations, but they must have high accuracy to do not compromise evaluation. The Gaussian Mixture Models (GMM) can be a good option to do an online evaluation, because they can obtain good accuracy models and they are simple too. However, according to Tran et al. [22] Relaxation Labeling methods offer best performances for classification problems. In their paper, they used Gaussian Mixture Models followed by Relaxation Labeling for speaker recognition with better performance over Gaussian Mixture Models only. We propose the use of the methodology designed by Tran et al. [22] to improve performance of Gaussian Mixture Models for an online training evaluator in virtual reality simulators.

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 [24]. 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 quality of the user experience in a virtual reality world is given by the graphics resolution and by the use of special devices for interaction. Basically, the devices stimulate the human senses as vision, audition and touch: head-mounted displays (HMD) or even conventional monitors combined with shutter glasses can provide stereoscopic visualization; multiple sound sources positioned provides 3D sound; and touch can be simulated by the use of haptic devices [16,8].

There are many purposes for virtual reality systems, but a very important one is the simulation of procedures for training. Virtual reality systems for training provide significant benefits over other methods, mainly in critical procedures. One example of training based on VR systems is the flight simulators used for the pilots' training in the civil aviation [23]. 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 [25], prostate examination [1], ocular surgery [9] and bone marrow harvest [6]. In some cases, the procedures are done without visualization for the physician, and the only information he receives is done by the tactile sensations provided by a robotic device with force feedback. These devices can measure forces and torque applied during the interaction [10] and these data can be used in an evaluation [5,18].

[1] Ronei Marcos de Moraes, Statistics Department, Federal University of Paraíba, Cidade Universitária s/n CEP 58.051-900 João Pessoa – PB - Brazil, tel.: +55 83 216-7075, ronei@de.ufpb.br
[2] Liliane dos Santos Machado, Laboratory of Integrated Systems - Polytechnic School - University of São Paulo, Av. Prof. Luciano Gualberto, 158. Trav.3. CEP: 05508-9010 - São Paulo - SP - Brazil, tel.: +55 11 3818-5676, liliane@lsi.usp.br

EVALUATION IN VIRTUAL REALITY SIMULATORS

The evaluation of simulations is necessary to assess 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 [21]. So, virtual reality systems can use one or more variables, as the mentioned above, to evaluate a simulation performed by user.

Some simulators for training have a method of evaluation. However they just compare the final result with the expected one or are videotape records post-analyzed by an expert [1]. Recently, some models for offline or online evaluation 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. [5,7] proposed the use of a fuzzy rule-based system to online evaluation of training in virtual worlds. Moraes and Machado [13] proposed the use of CHMM for online evaluation in any virtual reality simulators. After that, the same authors proposed another approach for online evaluation learning using Fuzzy Hidden Markov Models (FHMM) [14]. Using an optoelectronic motion analysis and video records, McBeth et al. [11] acquired and compared postural and movement data of experts and residents in different contexts by use of distributions statistics.

We are proposing the use of Gaussian Mixture Models and Relaxation Labeling (GMM-RL) to provide an online evaluation for simulators or training systems based on virtual reality. To test the method proposed, we are using a bone marrow harvest simulator [6]. 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 force feedback to give to the user the tactile sensations felt during the penetration of the patient's body [12]. 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 evaluation tool proposed should supervise the user movements during the puncture and should evaluate the training according to N possible classes of performance.

GAUSSIAN MIXTURE MODELS (GMM)

This section presents the Gaussian Mixture Models (GMM) method for training evaluation. Parameter estimation equations for training expert models are presented first. After, the GMM method for training classification is then described as a maximum likelihood classifier. We follow the Tran et al. [22] explanation about GMM algorithm and classification.

Let $X=\{x_1, x_2,...,x_T\}$ be a set of T vectors, where each one is a d-dimensional feature vector extracted by T different information at virtual space, obtained by the simulator. These information can be applied forces, angles, position and torque extracted at d different interval of time. Since the distribution of these vectors is unknown, it is approximately modeled by a mixture of Gaussian densities as the weighted sum of c component densities, given by the equation

$$p(x_t\,|\lambda_k) = \sum^{c}_{i=1} w_i\, N(x_t, \mu_i, \Sigma_i) \tag{1}$$

where λ denotes a prototype consisting of a set of model parameters $\lambda = \{w_i, \mu_i, \Sigma_i\}$, w_i, $i=1,...,c$ are the mixture weights and $N(x_t, \mu_i, \Sigma_i)$ are the d-variate Gaussian component densities with mean vectors μ_i and covariance matrices Σ_i:

$$N(x_t, \mu_i, \Sigma_i)=exp\{-1/2\,\}(x_t - \mu_i)'\, \Sigma_i^{-1}\, (x_t - \mu_i)\}\, /\, (2\pi)^{d/2}\, |\Sigma_i\,|^{1/2} \tag{2}$$

To train the GMM, these parameters are estimated such that they best match the distribution of the training vectors. The maximum likelihood estimation is widely used as a training method. For a sequence of training vectors X for a λ, the likelihood of the GMM is done by:

$$p(X|\lambda) = \Pi^{T}_{t=1}\; p(x_t\,|\lambda) \tag{3}$$

The aim of maximum likelihood estimation is to find a new parameter model $\bar{\lambda}$ such that $p(X|\,\bar{\lambda})\geq p(X|\lambda)$. Since the expression in (3) is a nonlinear function of parameters in λ, its direct maximization is not possible. However, these parameters can be obtained iteratively using the Expectation--Maximization algorithm [2]. In this algorithm, we use an auxiliary function Q done by:

$$Q(\lambda,\ \bar{\lambda})=\sum^{T}_{t=1} \sum^{c}_{i=1} p(i|x_t, \lambda)\, log\, [\, w_i\, N(x_t,\ \bar{\mu}_i,\ \bar{\Sigma}_i)] \tag{4}$$

where $p(i|x_t,\ \lambda)$ is the *a posteriori* probability for performance class i, $i=1,...,c$ and satisfies

$$p(i|x_t, \lambda) = [\, w_i\, N(x_t, \mu_i, \Sigma_i)]\, /\, \{\sum^{c}_{k=1}\ w_k\, N(x_t, \mu_k, \Sigma_k)\} \tag{5}$$

The Expectation--Maximization algorithm is such that if $Q(\lambda,\ \bar{\lambda})\geq Q(\lambda,\lambda)$ then $p(X|\ \bar{\lambda})\geq p(X|\lambda)$ [17]. Setting derivatives of the Q function with respect to $\bar{\lambda}$ to zero, we found the following reestimation formulas:

$$\bar{w}_i = 1/T \sum^{T}_{t=1}\ p(i|x_t, \lambda) \tag{6}$$

$$\bar{\mu}_i = \sum^{T}_{t=1} [\, p(i|x_t, \lambda)x_t\,]\, /\, [\sum^{T}_{t=1} [\, p(i|x_t, \lambda)] \tag{7}$$

$$\bar{\Sigma}_i=\{\Sigma^T_{t=1}\,[\,p(i|x_t,\,\lambda)(x_t-\,\bar{\mu}_i)\,(x_t-\,\bar{\mu}_i)'\}\,/\,[\Sigma^T_{t=1}\,[\,p(i|x_t,\,\lambda)] \tag{8}$$

The algorithm for training the GMM is described as follows:

1. Generate the *a posteriori* probability $p(i|x_t, \lambda)$ at random satisfying (5);

2. Compute the mixture weight, the mean vector, and the covariance matrix following (6), (7) and (8);

3. Update the a posteriori probability $p(i|x_t, \lambda)$ according to (5) and compute the Q function using (4);

4. Stop if the increase in the value of the Q function at the current iteration, relative to the value of the Q function at the previous iteration is below a chosen threshold, otherwise go to step 2.

The GMM classification

To provide GMM classification, we need several classes of performance λ. So, let λ_k, $k=1,...,N$, denote models of N possible classes of performance. Given a feature vector sequence X, a classifier is designed to classify X into N classes of performance by using N discriminant functions $g_k(X)$, computing the similarities between the unknown X and each class of performance λ_k and selecting the class of performance λ_{k^*} if [22]:

$$k^* = \underset{1\le k\le N}{\arg\max}\; g_k(X) \tag{9}$$

In the minimum--error--rate classifier, the discriminant function is the *a posteriori* probability:

$$g_k(X)=p(\lambda_k|X) \tag{10}$$

We can use the Bayes' rule

$$p(\lambda_k|X) = [p(\lambda_k)\, p(X|\lambda_k)] \,/\, p(X) \tag{11}$$

and we can assume equal likelihood of all performances, i.e., $p(\lambda_k)=1/N$. Since $p(X)$ is the same for all performance models, the discriminant function in (10) is equivalent to the following [4]:

$$g_k(X)=p(X|\lambda_k) \tag{12}$$

Finally, using the log--likelihood, the decision rule used for class of performance identification is:

Select performance model k if*

$$k^* = \underset{1\le k\le N}{\arg\max}\; \Sigma^T_{t=1}\; p(x_t|\lambda_k) \tag{13}$$

where $p(x_t|\lambda_k)$ is given by (1) for each k, $k=1,...,N$.

RELAXATION LABELING

The Relaxation Labeling (RL) was introduced by Rosenfeld et al. [20] and it is an interactive approach to update probabilities of a previous classification. This methodology is successfully employed in image classification [3]. In this case, we will use RL after applied GMM classification. So, let be a set of objects $A = \{a_1,a_2,...,a_N\}$ and a set of labels $\Lambda=\{\lambda_1,\lambda_2,...,\lambda_N\}$. An initial probability is given to each object a_t having each label λ_k, which is denoted by $p_t(\lambda_k)$. These probabilities satisfy the following condition:

$$\Sigma^N_{k=1}\; p_t(\lambda_k) = 1, \text{ for all } a_t \in A \tag{14}$$

The RL updates the probabilities $p_t(\lambda_k)$ using a set of compatibility coefficients $r_{tt'}\,(\lambda_k,\,\lambda_l)$, where $r_{tt'}\,(\lambda_k,\,\lambda_l)$: $\Lambda\times\Lambda\rightarrow[-1,1]$, whose magnitude denotes the strength of compatibility. The meaning of these compatibility coefficients can be interpreted as [22]:

a) If $r_{tt'}\,(\lambda_k,\,\lambda_l) < 0$, then λ_k, λ_l are incompatible for a_t *and* $a_{t'}$;
b) If $r_{tt'}\,(\lambda_k,\,\lambda_l) = 0$, then λ_k, λ_l are independent for a_t *and* $a_{t'}$;
c) If $r_{tt'}\,(\lambda_k,\,\lambda_l) > 0$, then λ_k, λ_l are compatible for a_t *and* $a_{t'}$;

For computing coefficients, two possible methods employ the concepts of statistical correlation and mutual information. The two methods are based on those developed by Peleg and Rosenfeld [15]. The correlation-based estimate of the compatibility coefficients is defined as

$$r_{tt'}(\lambda_k)(\lambda_l) = \{\Sigma^T_{t=1}\,[p_t(\lambda_k)-\,p(\lambda_k)][p_{t'}(\lambda_l)-\,p(\lambda_l)]\}/\{\sigma(\lambda_k)\sigma\,(\lambda_l)\} \tag{16}$$

where $p_t(\lambda_l)$ is the probability of $a_{t'}$ having label λ_l and $a_{t'}$ are the neighbors of $a_{t'}$, $p(\lambda_l)$ is the mean of $p_t(\lambda_l)$ for all $a_{t'}$, and $\sigma\,(\lambda_l)$ is standard deviation of $p_t(\lambda_l)$. To alleviate the effect of dominance among labels, the modified coefficients are [22]:

$$r^*_{tt'}(\lambda_k)(\lambda_l) = [1-\,p(\lambda_k)]\;[1-\,p(\lambda_l)]\;r_{tt'}(\lambda_k)(\lambda_l) \tag{17}$$

and the mutual-information based estimate of compatibility coefficient is

$$r_{tt'}(\lambda_k)(\lambda_l) = \log\,\{T\,\Sigma^T_{t=1}\,p_t\,(\lambda_k)\,p_{t'}(\lambda_l)\}\,/\,\{\Sigma^T_{t=1}\,p_t\,(\lambda_k)\,p_{t'}(\lambda_l)\} \tag{18}$$

The compatibility coefficients in (18) must be scaled in the range [-1,1].

The updating factor for the estimate $p_t(\lambda_k)$ at m[th] interaction is:

$$q_t^{(m)}(\lambda_k)= \Sigma^{T}_{t'=1}\ d_{tt'}\ [\Sigma^{N}_{l=1}\ r_{tt'}(\lambda_k)(\lambda_l)\ p_{t'}^{(m)}(\lambda_l)] \qquad (19)$$

where $d_{tt'}$ are the parameters that weight the contributions to a_t coming from its neighbors $a_{t'}$ and subject to

$$\Sigma^{T}_{t'=1}\ d_{tt'} = 1 \qquad (20)$$

The updated probability $p_t^{(m+1)}(\lambda_k)$ for object a_t is given by:

$$p_t^{(m+1)}(\lambda_k) = \{p_t^{(m)}(\lambda_k)[1+ q_t^{(m)}(\lambda_k)]\} \ / \ \{\Sigma^{N}_{k=1}\ p_t^{(m)}(\lambda_k)[1+ q_t^{(m)}(\lambda_k)]\} \qquad (21)$$

The RL algorithm can be outlined as follows:

1. Estimate the initial probabilities for each object satisfying (14)
2. Compute the compatibility coefficients using (17) or (18)
3. Calculate the updating factor defined in (19)
4. Update the probabilities for each object using the updating rule in (21)
5. Repeat steps 3 and 4 until the change in the probability is less than a chosen threshold or equal to a chosen number of interactions.

THE GMM-RL CLASSIFICATION

It now becomes clear that for a successful performance of relaxation method process, the initial label probabilities and the compatibility coefficients need to be well determined. Wrong estimates of these parameters will lead to algorithmic instabilities. In the GMM-based classification, the initial probabilities in the RL are defined as the *a posteriori* probabilities. Objects are now features vectors considered in the GMM and labels are classes of performance identification. Unlike the relaxation labeling for image recognition where the m-connected neighboring pixels may belong to different regions, in performance identification, all unknown feature vectors in the sequence $X=\{x_1, x_2,...,x_T\}$ are known to belong to a certain class of performance λ. Therefore there is no need to considerer the compatibility between an input vector and its adjacent vectors [22]. This leads to:

$$p_{t'}(\lambda_l) = p_t(\lambda_l) \qquad (22)$$

which means that compatibility between different labels is only considered for same object and therefore the updating rule in (21) should be now rewritten [22] as follows:

$$p_t^{(m+1)}(\lambda_k) = \{p_t^{(m)}(\lambda_k)[1- q_t^{(m)}(\lambda_k)]\} \ / \ \{\Sigma^{N}_{k=1}\ p_t^{(m)}(\lambda_k)[1- q_t^{(m)}(\lambda_k)]\} \qquad (23)$$

The GMM-RL algorithm for class of performance identification is stated as follows.

1. Estimate the initial probabilities for each class of performance using the a posteriori probabilities in (3):

$$p_t(\lambda_k) = p(\lambda_k|x_t)= [p(x_t\ |\lambda_k)\ p(\lambda_k)] \ / \ [\ \Sigma^{N}_{k=1}\ p(x_t\ |\lambda_k)\ p(\lambda_k)] \qquad (24)$$

where $p(\lambda_k)=1/N$ and $p(x_t\ |\lambda_k)$ is computed as in (1)

2. Compute the compatibility coefficients using (17) or (18), where $t'=t$ (no neighbors considered);
3. Calculate the updating factor defined in (19), where $t'=t$ and $d_{tt'}=1/T$ for simplicity;
4. Update the probabilities for each class of performance using the updating rule in (23);
5. Repeat steps 3 and 4 until the change in the probability is less than chosen threshold or equal to a chosen number of interactions;
6. The probability of each class of performance $p(\lambda_k)$ after RL algorithm is computed by:

$$p(\lambda_k) = \Pi^{T}_{t=1}\ p_t(\lambda_k) \qquad (25)$$

where $p_t(\lambda_k)$ is the a posteriori probability used in (10). Therefore, the decision rule for class of performance identification is as follow [22]:

Select class of performance k if*

$$k^* = \underset{1\le k\le N}{\arg\max}\ p(\lambda_k) \qquad (26)$$

THE EVALUATION TOOL

The evaluation tool proposed should supervise the user movements and others parameters associated to it. In the virtual reality simulator the trainee must extract the bone marrow. In the first movement, he must feel the skin to find the best place to insert the needle. 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 system the trainee movements are monitored by variables as: acceleration, applied force, spatial position, torque and angles of needle.

For the evaluation an expert executes several times the procedure for each class of performance available, for example: "well qualified", "need some training yet", "need more training", "novice", etc. So, the information of variability about these procedures is acquired using Gaussian Mixture Models and Relaxation Labeling (GMM-RL). When a trainee uses the system his performance is compared with the *N* classes of performances and a probability of trainee's performance for each class of performance is calculated using (24). Finally, according to (26) trainee's performance is labeling and trainee receives a report with all possible classes of performance and its respective probabilities about his performance.

Conclusions and Future Works

In this paper we presented a new approach to online evaluation in training simulators based on virtual reality using an elegant statistical formalism of GMM-RL. This approach provides the use of continuous variables without lost of information. So, it solves the problem of low complexity of online evaluators, without compromise performance of simulator and with good accuracy evaluation.

Systems based on this approach can be applied in virtual reality simulators for several areas and can be used to classify the trainee into classes of learning giving him a real position about his performance, through the reports of performance of each training. In medicine, it provides an appropriate methodology for blind made procedures.

As future work, we intend to make a statistical comparison between two groups of trainees when they use or not use this system to determine differences in the increasing of learning.

References

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

[2] Dempster, A. P., Laird, N. M., Rubin, D. B., Maximum Likelihood from Incomplete Data via EM Algorithm. *Journal of Royal Statistical Society, Ser. B*. v. 39, pp.1-38, 1977.

[3] Fu, K. S.; Yu, T. S., *Statistical Pattern Classification Using Contextual Information*. Research Studies Press, 1980.

[4] Johnson, R. A. and Wichern, D. W., *Applied Multivariate Statistical Analysis*. Prentice Hall, 1998.

[5] 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.

[6] 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 - Medicine Meets Virtual Reality*, vol. 81, pp.293-297, January, 2001.

[7] Machado, L. S., Zuffo, M. K., Moraes, R. M. and Lopes, R. D., Haptic Modeling, Stereoscopic Visualization and Evaluation Aspects in a Simulator for Bone Marrow Harvest for Transplant. *Proceedings of the 4th SBC Symposium on Virtual Reality*, pp. 23-31, Brazil, 2001. (in portuguese)

[8] Mahoney, D.P. The Power of Touch. *Computer Graphics World*, v.20, n. 8, p. 41-48, August, 1997.

[9] Mahoney, D.P. The Eyes Have It. *Computer Graphics World*, v. 21, n. 8, p. 69-70, August 1998.

[10] Massie, T., Salisbury, K., The PHANToM Haptic interface: A device for probing virtual objects. *ASME Winter Annual Meeting*, DSC. v. 55-1. pp. 295-300. 1994.

[11] McBeth, P. B. et al., Quantitative Methodology of Evaluating Surgeon Performance in Laparoscopic Surgery. *Studies in Health Technology and Informatics: Medicine Meets Virt. Real.*, v 85, pp280-286, Jan., 2002.

[12] Moody, L., Baber, C., Arvanitis, T. N., Objective Surgical Performance Evaluation Based on Haptic Feedback. *Studies in Health Technology and Informatics: Medicine Meets Virt. Real.*, v 85, pp304-310, Jan., 2002.

[13] Moraes, R. M., Machado, L. S., Hidden Markov Models for Learning Evaluation in Virtual Reality Simulators. *Anals of 2002 IASTED International Conference on Computers and Advanced Technology in Education*, pg 405-409, Mexico, 2002.

[14] Moraes, R. M., Machado, L. S., Fuzzy Hidden Markov Models for Online Training Evaluation in Virtual Reality Simulators. in *Computational Intelligent Systems for Applied Research*. World Scientific, Singapore, pp296-303, 2002.

[15] Peleg, S.; Rosenfeld, A., "Determining Compatibility Coefficients for Curve Enhancement Relaxation- Process". *IEEE Trans. on Systems, Man and Cybernetics*, v. 8(7), pp548-555, 1978..

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

[17] Rabiner, L. R., A Tutorial on Hidden Markov Models and Selected Application in Speech Recognition. *Proceedings of the IEEE*, v77(2), 1989.

[18] Rosen J., Richards, C., Hannaford, B. and Sinanan, M., Hidden Markov Models of Minimally Invasive Surgery, *Studies in Health Technology and Informatics: Medicine Meets Virt. Real.*, v 70, pp279-285, Jan., 2000.

[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: Medicine Meets Virt. Real.*, v 81, pp417-423, Jan., 2001.

[20] Rosenfeld, A., Hummel, R. A., Zucker, S. W., Scene labelling by relaxation operations. *IEEE Transactions on Systems, Man and Cybernetics*, v. 6(6), pp. 420-433, 1976.

[21] Salisbury, K. Haptics: The Technology of Touch. *HPCWire Special*, nov 1995, n. 10.

[22] Tran, D., Pham, T., Wagner, M., Speaker recognition using Gaussian mixture models and relaxation labeling. in *Proceedings of the 3rd World Multiconference on Systemetics, Cybernetics and Informatics/ The 5th Int. Conf. Information Systems Analysis and Synthesis* (SCI/ISAS99), vol. 6, pp. 383-389, 1999.

[23] Villano, M. *The Virtually Real Thing*. Internet site: http://future.newsday.com/6/fmon0628.htm. Acess in 22/july/2002.

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

[25] Voss, G.; Brockholt, U.; Los Arcos, J.; Müller, W.; Oppelt, P.; Stäler, J. Lahystotrain – Intelligent Training System for Laparoscopy and Hysteroscopy. *Studies in Health Technology and Informatics - Medicine Meets Virtual Reality*, n. 70, p. 359-364. Jan. 2000.