FUZZY HIDDEN MARKOV MODELS FOR ONLINE TRAINING EVALUATION IN VIRTUAL REALITY SIMULATORS

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A new approach to evaluate training in simulators based on virtual reality is proposed. This approach uses Fuzzy Hidden Markov Models (FHMM) for modeling and classification of the simulation in pre-defined classes of training.

1 Introduction

Nowadays, several kinds of training are made in virtual worlds. As example, military procedures, medical surgeries and critical procedures can be mentioned. Very realistic virtual reality environments are constructed with training objectives to immerge the user into virtual world. However, it is very important to know what is the quality of the training and what is the trainee's performance. It is important too, the existence of an online evaluation for the trainee evaluation and improvement of his learning.

In medicine, some models for offline or online evaluation of training have been proposed. Rosen *et al.*[13] proposed the use of Discrete Hidden Markov Models (DHMM) to modeling forces and torque during a simulated training in a porcine model. However, this approach is deficient, because uses discrete HMM to modeling continuous variables. One year latter, Rosen *et al.*[14] corrected it and proposed the use of Continuous Hidden Markov Models (CHMM) to modeling forces and torques, but uses distance between HMMs to evaluate the training. Both works[13,14] were used to evaluate laparoscopic surgical skills. Machado *et al.*[6,8] proposed the use of a fuzzy rule-based system to online evaluation of training in virtual worlds. This system uses forces, positions and angles to trainee evaluation and it was used to evaluate a bone marrow harvest for transplant simulator.

In online evaluation for virtual reality simulators we have some problems. Virtual worlds are approaches of real worlds, thus we do not have an exact measure correspondence between both. In medicine, the states in some minimally invasive procedures are not observed because they are executed blindly. The first problem can be solved using a fuzzy approach and the second problem can be solved using the approach of Continuous Hidden Markov Models (CHMM). In this paper we propose to join both approaches using Fuzzy Hidden Markov Models (FHMM) in a way similar to the one proposed by Tran and his colleagues[16] to online evaluation of medical procedures in virtual worlds. In their original paper[16], FHMM was used to speech and speaker recognition and was shown the effectiveness of this fuzzy approach to classical HMM.

2 Training and Virtual Reality Worlds

Virtual Reality refers to real-time systems modeled by computer graphics that allow user interaction and movements with three or more degrees of freedom[17]. More than a technology, virtual reality became a new science that joins several fields as computers, 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. There are many purposes for virtual reality systems, but a very important one is the simulation of procedures for training. Training simulation provides significant benefits over other methods, mainly in critical procedures. 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. The evaluation of simulations is necessary to assess the training quality and provide some feedback about the user performance. User movements, applied forces, angles, position and torque can be collected from haptic devices and be used in an evaluation[6,13]. Spatial movements can be collected from mouse, keyboard and any other tracking device. Robotic devices, some of them capable to provide tactile feedback to the user, can measure forces and torque applied during the interaction[10]. So, virtual reality systems can use one or more variables to evaluate a simulation performed by a user.

3 Online Evaluation in Virtual Reality Simulators

In medicine, there are many procedures performed without any visual information for the physician. One example is the internal exams as prostate examination in which the touch is the only sense used. The training of these procedures generally are performed by the use of plastic models, cadavers or guinea pigs. It allows a limited manipulation and depends on the availability of the material. But, the most significant detail is that these materials do not represent the exact features of the human body, even when cadavers are used due to tissue degradation[3]. Based on these observations, we believe that virtual reality systems are very beneficial in simulations for training. It seems to be more obvious when haptic devices can be used allowing the sense of touch for simulation of procedures without visual information[9]. In these cases, an evaluation tool could supervise the user movements during the internal manipulation of the object. Some simulators for training have a method of evaluating. However they just compare the final result with the expected one or are videotape records post-analyzed by an expert[2]. We are proposing the use of fuzzy hidden-markov models to provide an online evaluation for simulators or training systems. To tests the method proposed, we are using a bone marrow harvest simulator[7].

3.1 The Bone Marrow Harvest Simulator

The bone marrow transplant is a relatively new medical procedure to treat recently considered incurable diseases. The process to extract the bone marrow is made through many material aspirations from the iliac crest bone marrow (sometimes it includes the sternum bone also) from a donator under general anesthesia. The procedure is done blindly, performed without any visual feedback except the external view of the donor body. So, 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 1 shows the layers trespassed by the needle. The simulator uses a robotic arm that operates with six degrees of freedom movements and force feedback in the x, y and z axis[7].

4 Hidden Markov Models (HMM) and Fuzzy Hidden Markov Models (FHMM)

4.1 Discrete and Continuous Hidden Markov Models

The basic theory of Hidden Markov Models (HMM) was published in the late 1960s by Baum and his colleagues[1]. Nowadays, discrete and continuous HMMs are commonly used in speech recognition[12]. Some other applications of HMM can be found for recognition of genes in DNA [5]; for skill acquisition from human demonstration[4]; and for recognition of cursive handwriting[18].

In the classical HMM, we need five elements to specify a discrete HMM[12]. Let us denote an HMM by $\lambda = (A, B, \pi)$, we need: (i) the number N of states

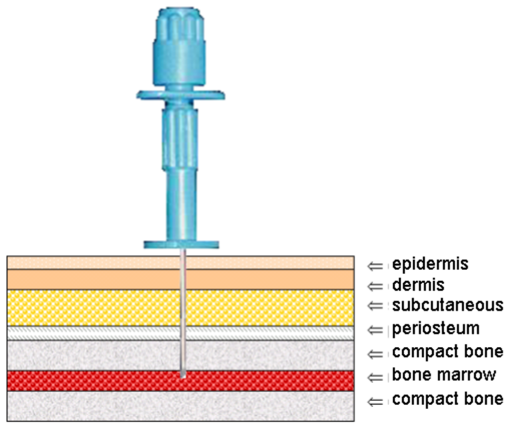

Figure 1. The tissue layers trespassed by needle in a bone marrow harvest.

in the model; (ii) the number M of distinct observation symbols per state, i. e. the discrete output of system; (iii) the state transition probability distribution matrix, denoted by $A = \{a_{ij}\}$; (iv) the observation symbol probability distribution in state j, denoted by $B = \{b_j(k)\}$ and (v) the initial state distribution $\pi = \{\pi_i\}$, where $1 \leq i, j \leq N$ and $1 \leq k \leq M$. Given the HMM form, there are three basic problems of interest that must be solved for the model to be useful in real applications. These problems are:

1 - Evaluation problem: Given the observation sequence in time $O = o_1, o_2, ..., o_T$ and a model λ, how do efficiently compute $P(O \mid \lambda)$, the probability of the observation sequence, given a model?

2 - Uncover the hidden part of the model: Given the observation sequence $O = o_1, o_2, ..., o_T$ and a model λ, how do we choose a corresponding state sequence $S = s_1, s_2, ..., s_T$ which is optimal in some meaningful sense (i.e., best "explains" the observations)?

3 - Optimize the model parameters: How do adjust the model parameters $\lambda = (A, B, \pi)$ to maximize $P(O \mid \lambda)$?

To solve the first problem, we can use the *Forward-Backward Procedure*[12]. The second problem appears when we have degenerated models or incomplete observations. It is an optimization problem and it can be solved using the *Viterbi Algorithm*[12]. The last problem can be solved by an iterative procedure such as the Baum-Welch method (or equivalently the EM method)[12].

For most applications, the observations are continuous vectors. We can use Vector Quantization (VQ) to generate codebooks and use DHMM. However, to do this we need training data for all classes. When a new class is added, we must to train the system from the beginning. In Continuous Hidden Markov Models (CHMM), we only need to train the newly added class. The densities are considered as a mixture of Gaussians:

$$b_j(o_t) = P(o_t \mid \lambda) = \sum_{k=1}^{M} w_{jk}\mathcal{N}(ot, \mu_{jk}, \Sigma_{jk})$$

where o_t, $t = 1, ..., T$ are observation vectors being modeled, w_{jk}, $j = 1, ..., N$, $k = 1, ..., M$ are mixture coefficients and $\mathcal{N}(ot, \mu_{jk}, \Sigma_{jk})$ is a Gaussian with mean vector μ_{jk} and covariance matrix Σ_{jk} for the kth mixture component in the state j and the following constrains are satisfied: $\forall w_{jk} > 0$; $\sum_{k=1}^{M} w_{jk} = 1$ and $\int_{-\infty}^{+\infty} b_j(o_t) do_t = 1$ An iterative reestimation process is used to found the coefficients. Rabiner[12] describes a procedure for providing good initial estimates of the model parameters called the segmental K-means.

4.2 Continuous Fuzzy Hidden Markov Models

In our system the virtual world is limited in the space. The observation vectors are continuous vectors (positions, angles, forces, torques, etc) and then we will focus ourselves in only the continuous version of Fuzzy HMM. We will follow the FHMM proposed by Tran and your colleagues[16]. Others fuzzy approach for HMM exists, such as done by Mohamed and Gader[11].

Let $u_{ijt} = u_{ijt}(O)$ be the membership function, denoting the degree to which, the observation sequence O belongs to state i at time t and to state j at time $t+1$, satisfying $0 \leq u_{ijt} \leq 1$; $\sum_{i=1}^{N}\sum_{j=1}^{N} u_{ijt} = 1$; and $0 < \sum_{t=1}^{T} u_{ijt} < T$.

Using the fuzzy EM Algorithm[15], it can be shown that the reestimation equations for coefficients of the mixture of densities done by Eq. (4.1) are:

$$\overline{w}_{jk} = \frac{\sum_{t=1}^{T} \overline{u}_{jkt}^{m}}{\sum_{t=1}^{T}\sum_{k=1}^{M} \overline{u}_{jkt}^{m}}, \qquad \overline{\mu}_{jk} = \frac{\sum_{t=1}^{T} \overline{u}_{jkt}^{m} o_t}{\sum_{t=1}^{T} \overline{u}_{jkt}^{m}}$$

$$\overline{\Sigma}_{jk} = \frac{\sum_{t=1}^{T} \overline{u}_{jkt}^{m} \left(o_t - \overline{\mu}_{jk}\right)\left(o_t - \overline{\mu}_{jk}\right)'}{\sum_{t=1}^{T} \overline{u}_{jkt}^{m}} \tag{1}$$

where the prime denotes vector transposition, $m \geq 1$ is a weighting exponent on each fuzzy membership $u_y(x)$ (and is called degree of fuzziness) and

$$
\begin{aligned}
\overline{u}_{jkt} &= \left\{ \sum_{i=1}^{N} \sum_{l=1}^{M} \left[\frac{d_{jkt}}{d_{ilt}} \right]^{\frac{2}{m-1}} \right\}^{-1}, \qquad && m > 1 \\
\overline{u}_{jkt} &= \eta_t(j,k), && m = 1
\end{aligned}
\tag{2}
$$

where

$$
\begin{aligned}
d_{jkt}^2 &= d_{jkt}^2(O) = -\log P(O, s_t = j, k_t = k \mid \lambda) \\
&= -\log \left\{ \sum_{i=1}^{N} \alpha_t(i) a_{ij} w_{jk} \mathcal{N}(o_t, \mu_{jk}, \Sigma_{jk}) \beta_{t+1}(j) \right\}
\end{aligned}
\tag{3}
$$

and

$$
\begin{aligned}
\eta_t(j,k) &= P(s_t = j, k_t = k \mid O, \lambda) \\
&= \frac{\alpha_t(j)\beta_t(j)}{\sum_{j=1}^{N} \alpha_t(j)\beta_t(j)} \times \frac{w_{jk}\mathcal{N}(o_t, \mu_{jk}, \Sigma_{jk})}{\sum_{k=1}^{M} w_{jk}\mathcal{N}(o_t, \mu_{jk}, \Sigma_{jk})}
\end{aligned}
\tag{4}
$$

where $\alpha_t(j)$ and $\beta_t(j)$ are the forward and backward respectively[12].

Let λ_z, $z = 1, ..., Z$ denote models of Z FHMMs modeled. Given a new feature vector sequence O' , we can classify O' of two different ways: (1) To verify the distances between each pair λ_z and λ'_O and find the smaller[12], or (2) To use a discriminant criteria, to classify O' into one of Z models[16].

5 The Evaluation Tool

The evaluation tool proposed should supervise the user movements and the 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. If the quantity of bone marrow is sufficient the proceeding finish, else he must find another position to extract bone marrow again. 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 correct procedure. So, the information of variability about this procedure is acquired using a Fuzzy Hidden Markov Model (FHMM). When a trainee uses the system his performance is compared with expert performances and a comparison coefficient of performances is obtained. This coefficient is normalized and works as a mark for trainee performance. Several classes of performances are available to give to trainee a position about his training, as: "you are well qualified", "you need some training yet", "you need more training" and "you are a novice".

6 Conclusions and Future Works

In this paper we presented a new approach to online training evaluation in virtual reality simulators. This approach has an elegant mathematical formalism of CHMM and Fuzzy Sets and solves the main evaluation problems in blind made procedures. In medicine, it is welcome because provides the use of continuous variables without lost of information and provides an appropriate fuzzy methodology to measures in virtual reality worlds. 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.

As future work, we pretend to make a statistical comparison between two groups of trainees when they use or not use this system to verify a possible increasing of learning.

References

1. Baum, L. E. and Petrie, T., Statistical Inference for Probabilistic Functions of Finite State Markov Chains. Ann Math. Stat., v.37, pp1554-1563, 1966.
2. 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.
3. Holton, L. L. H., Force Models for Needle Insertion Created from Measured Needle Puncture Data. Studies in Health Technology and Informatics: Medicine Meets Virt. Real., v 81, pp180-186, Jan., 2001.
4. Hovland, G. E., Sikka, P. and McCarragher, B. J., Skill acquisition from human demonstration using a hidden markov model. Proc. of IEEE Int. Conf. on Robotics and Automation, pp 2706-2711, 1996, USA.
5. Kulp, D., Haussler, D., Reese, M. G. and Eeckman, F.H., A generalized hidden Markov model for the recognition of human genes in DNA. Proceedings of ISMB-96. pp134-142, 1996.
6. 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
7. 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.
8. Machado, L. S., Zuffo, M. K., Moraes, R. M. and Lopes, R. D., Haptic Modeling, Sterescopic 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)
9. Mahoney, D.P. The Power of Touch. Computer Graphics World, v.20, n. 8, p. 41-48, August, 1997.
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. Mohamed, M. A. and Gader, P., Generalized Hidden Markov Models - Part I: Theoretical Frameworks. IEEE Trans. on Fuzzy Syst. v8(1), pp.67-81, 2000
12. Rabiner, L. R., A Tutorial on Hidden Markov Models and Selected Application in Speech Recognition. Proceedings of the IEEE, v77(2), 1989.
13. 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.
14. 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.
15. Tran, D., Wagner, M., Fuzzy Expectation-Maximization Algorithm for Speech and Speaker Recognition. In Proceedings of 18th International Conference of the North American Fuzzy Information Society (NAFIPS99). Pp421-425, 1999, USA.
16. Tran, D., Wagner, M. and Zheng, T., A Fuzzy Approach to Statistical Models in Speech and Speaker Recognition. In Proceedings of the FUZZ-IEEE99 Conference. v.3, pp.1275-1280, 1999, Khorea.
17. Vince, J. Virtual Reality Systems. Addison-Wesley, 1995.
18. Xiong, Y., Huo, Q. and Chan, C. A Discrete Contextual Stochastic Model for the Offline Recognition of Handwritten Chinese Characters. IEEE Trans. on Patt. Anal. and Mach. Intel. v.23(7), pp774-782, 2001.