Hidden Markov Models for Learning Evaluation in Virtual Reality Simulators

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ABSTRACT
Training on simulators systems based on virtual reality for learning or learning improvement may be a more cost-effective and efficient alternative to traditional training methods. A new approach for quality for online training evaluation in virtual reality simulators is proposed. This approach uses Hidden Markov Models (HMM) for modeling and classification of training in pre-defined classes of training. In this paper we show an example of application in a simulator of bone marrow harvest for transplant.

KEY WORDS
Hidden Markov Models, Online Learning Evaluation, Virtual Reality Worlds

1. Introduction

Introduction

In several works where life risk exists it is important the existence of a good training. As example, military procedures, medical surgeries and critical procedures can be mentioned. Nowadays, several kinds of training are made in virtual worlds. 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 learning and what is the trainees performance. It is important too, the existence of an online evaluation tool for the trainee evaluation and improvement of his learning.

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 and when high costs are included. In these cases, training on simulators systems may be a more cost-effective and efficient alternative to traditional training methods. 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. One example are the procedures performed without any visual information for the physician, as the prostate examination, 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. That 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 [6]. 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 [15]. In these cases, an evaluation tool could supervise the user movements during the internal manipulation of the object.

A method of evaluating can be found in some simulators for training in medicine. However they just compare the final result with the expected one or are videotape records post-analyzed by an expert [3]. Some models for offline or online evaluation of training have been proposed. Rosen et al.[19] proposed the use of Discrete Hidden Markov Models (HMM) 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.[20] corrected it and proposed the use of Continuous Hidden Markov Models (CHMM) to modeling forces and torque, but used distance among HMMs to evaluate the training in a porcine model. Both works [19, 20] are used to evaluate laparoscopic surgical skills. Machado et al.[12, 14] proposed the use of a fuzzy rule-based system to online evaluation of quality of training in virtual reality worlds. This system uses forces, positions and angles to trainee evaluation and it was used to assess user performance in a bone marrow harvest for transplant simulator [13].

In online evaluation in virtual worlds 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 surgery are not observed because the procedures are blind made. We can solve the first problem using a statistical approach of continuous variables observed in training. The second problem we can solve using Continuous Hidden Markov Models (CHMM). In CHMM, we can model systems which we can not observe the states directly, but functions of them [17].

We propose the use of Hidden Markov Models (HMM) to online training evaluation in virtual worlds. Usually, HMM was used to off-line speech and speaker recognition [17, 22] and recently in off-line evaluation training in medical procedures using porcine model (pig) [19, 20]. Some other applications of HMM can be found in [10] for the recognition of human genes in DNA; [7] for skill acquisition from human demonstration; [11] for automatic recognition of facial expressions and [4, 5, 24, 25] for the recognition of cursive handwriting.

This work is organized as follows. Section 2 presents the basic concepts of Discrete and Continuous Hidden Markov Models. Section 3 presents details about training into virtual reality worlds and evaluation in virtual reality simulators. Section 4 presents an implementation of an evaluation tool using HMM. Finally, Section 5 brings the conclusion and suggestions to future works.

2. Hidden Markov Models (HMM)

2.1 Discrete Hidden Markov Models (DHMM)

The basic theory of Hidden Markov Models (HMM) was published in the late 1960s and early 1970s by Baum and his colleagues [1, 2]. In the classical HMM we need five elements to specify a discrete HMM [17]. Let us denote an HMM by $\lambda = (A, B, \pi)$, we need: (i) the number N of states 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 [17]. The second problem is an optimization problem and it can be solved using the Viterbi Algorithm [21]. The last problem can be solved by an iterative procedure such as the Baum-Welch Method (or equivalently the EM - expectation-maximization - method) [17]. In next sections, we follow notation used by Rabiner [17].

2.2 Continuous Hidden Markov Models (CHMM)

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

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

where o_t, $t = 1, ..., T$ are observation vectors being modeled, w_{jk}, $j = 1, ..., N$, $k = 1, ..., M$ are mixture coefficients and $\mathcal{N}(o_t, \mu_{jk}, \Sigma_{jk})$ is a Gaussian with mean vector μ_{jk} and covariance matrix Σ_{jk} for the kth mixture component in the state j, done by:

$$\begin{aligned} \mathcal{N}(o_t, \mu_{jk}, \Sigma_{jk}) = & \frac{1}{(2\pi)^{N/2} \left|\Sigma_{jk}\right|^{1/2}} \times \\ \times \quad & \exp\left\{-\frac{1}{2}(o_t - \mu_{jk})' (\Sigma_{jk})^{-1} (o_t - \mu_{jk})\right\} \end{aligned} \qquad (2)$$

and the following constrains are satisfied:

$$w_{jk} > 0; \quad \sum_{k=1}^{M} w_{jk} = 1; \quad \int_{-\infty}^{+\infty} b_j(o_t) do_t = 1 \qquad (3)$$

An iterative reestimation process is used to found the coefficients. Rabiner [17] describes a procedure for providing good initial estimates of the model parameters called the segmental K-means [9]. It is a variant of the classical K-means algorithm [8] for clustering data.

2.3 Comparison of Hidden Markov Models

In this work, it is important to compare two HMMs. Let be $\lambda_1 = (A_1, B_1, \pi_1)$ and $\lambda_2 = (A_2, B_2, \pi_2)$, two different HMMs, we wish a measure of similarity of two models. We can use the concept of distance measure, denoted by $D(\lambda_1, \lambda_2)$ between two HMMs, as

$$D(\lambda_1, \lambda_2) = \frac{1}{T}\left[\log P(O^{(2)} \mid \lambda_1) - \log P(O^{(2)} \mid \lambda_2)\right] \quad (4)$$

where $O^{(2)} = O_1, O_2, ..., O_T$ is a sequence of observations generated by model λ_2. Thus, equation 4 is a measure of how well model λ_1 matches observations generated by λ_2, relative to how well model λ_2 matches observations generated by itself [17]. Unfortunately, this measure is nonsymmetrical. Hence a natural expression for this measure is the symmetrized version:

$$D_s(\lambda_1, \lambda_2) = \frac{D(\lambda_1, \lambda_2) + D(\lambda_2, \lambda_1)}{2} \quad (5)$$

3. 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 [23]. 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 total 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 based on virtual reality is necessary to measure the training quality and provide some feedback about the user performance too. User movements, applied forces, angles, position and torque can be collected from the devices and be used in an evaluation [12, 19]. 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 [16]. So, virtual reality systems can provide one or more variables, as the mentioned above, to assess a simulation performed by a user.

3.1 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 [6]. 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 [15]. 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 [3]. We are proposing the use of fuzzy hidden-markov models to provide an online evaluation for simulators or training systems. To test the method proposed, we are using a bone marrow harvest simulator [13].

3.2 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 a blind procedure 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 [13]. The robotic arm represents the needle used in a real procedure and visualized in the virtual world of the simulation.

4. The Evaluation Tool

The evaluation tool proposed should supervise the user movements and the parameters associated to it. During the simulation the trainee must extract the bone marrow. In a first movement, he must determine the best place to insert the needle. After the needle inser-

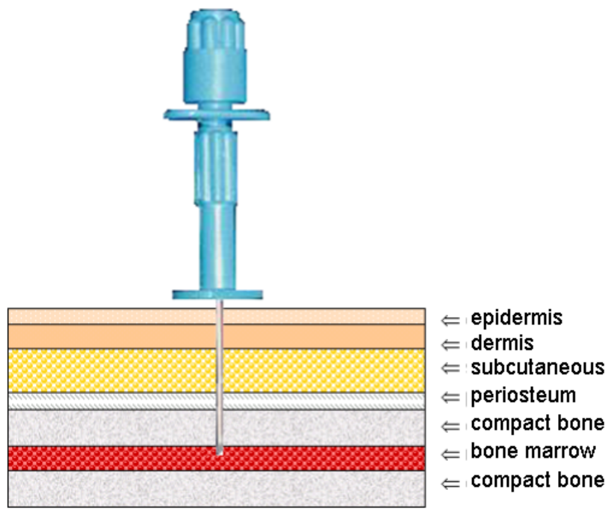

Figure 1. The tissue layers trespassed by needle in a bone marrow harvest.

tion be started, he must feel the tissue layers (epidermis, dermis, subcutaneous, periosteum and compact bone) trespassed by the needle and stop to do the bone marrow extraction. If the quantity of bone marrow is sufficient the procedure stops, else he must find another position to extract bone marrow again. During these steps the trainee movements are monitored by variables as: acceleration, applied force, spatial position, torque and angles of needle. The figure 2 shows the robotic arm used in the system and used to collect the user movements variables.

Figure 2. The robotic arm used in the bone marrow harvest simulator.

For the evaluation an expert executes several times the correct procedure. So, the information of variability about these procedures is acquired and stored using an Hidden Markov Model (HMM). When a trainee uses the system his performance will be compared with expert performances and a comparison coefficient of performances is obtained. This coefficient is normalized and works as a mark for trainee learning. Several classes of performance 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".

5. Conclusions and Future Works

In this paper we present a new approach to online training evaluation in virtual reality worlds. This approach has an elegant mathematical formalism of CHMM and solves the main evaluation problems in blind made procedures: it is online evaluation, it is impartial and it provides an internal analysis of procedure. In medicine, this approach is welcome, because provides a continuous approach to variables without lost of information and provides an online learning evaluation in virtual reality spaces. This methodology can be used for training evaluation in several classes of virtual reality systems and we show how to use this approach in learning evaluation of bone marrow harvest for transplant.

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.

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