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Detecting changes in motion characteristics during sports training

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Abstract— **This paper proposes a stochastic approach for representing and analyzing the gradual changes that occur in human movement during sports training. Human movement primitives are described using Factorial Hidden Markov Models, and compared using the Kullback-Liebler distance, a measure of information divergence between two models. This representation is combined with an automated segmentation and clustering approach to enable the system to autonomously extract and group together movement primitives from continuous observation of human movement data. The proposed system is tested on a human movement dataset obtained over 4 months during training for a marathon. Experimental results demonstrate that the system is able to detect gradual changes in the human movement.**

I. INTRODUCTION

Human movement is complex and varied, and undergoes significant changes over the lifetime of each individual. As physical capabilities change, the quality of the movement also changes. These changes could be attributed to the aging process, disease progression, rehabilitation following an illness, or movement improvements due to sports and other training. These changes are multifaceted and interrelated, involving changes in movement duration, extension, and variability. In this paper, we propose an approach for quantitatively measuring and tracking changes in the quality of movement over time, based on a stochastic characterization of the time series sequence comprising the movement. The approach is general and automated, and has potential applications to rehabilitation, diagnosis and sports training.

Recently, there has been increased interest in the use of Artificial Intelligence and other computational methods for automatic analysis of human motion [1]. In particular, gait analysis for gait classification and human identification through gait has received significant attention in the literature [2], [3], [4], [5], [6]. Many different techniques have been proposed, including recognition based on image based information [4], Principal Components Analysis (PCA) [5], [6], and Hidden Markov Models [3]. In addition, neural networks have also been considered for recognition of sports movements, such as running, squash and rowing [7], [8].

However, most of the approaches proposed to date rely on manual preparation of the data and an off-line training component to train the system for recognition. Therefore, the motion which can be analyzed must be specified a-priori, introducing a significant limitation to the system. A second issue with these systems is that the motions being classified consist of a discrete set of motions, which are assumed to be static. However, in applications such as rehabilitation and sports training, the analyst is interested in monitoring the change in the motion pattern over time.

In this paper, we investigate the use of Factorial Hidden Markov Models (HMMs) [9], [10] to represent human movement primitives during sports training. A simple HMM is a stochastic model capable of describing both the temporal and spatial variability of a motion. A Factorial HMM (FHMM) is a similar model incorporating a distributed description of the state, giving the FHMM an improved capability for movement representation and discrimination among similar motions. Motions described as FHMM or HMM models can be compared based on the Kullback-Liebler distance, a measure of information divergence between two models. FHMMs provide improved representation and discriminative power, and are able to distinguish between similar motions [10]. We use an automated segmenting and clustering system [11], [12] for automatic human motion analysis. The proposed system is capable of extracting motion segments from a continuous on-line demonstration, and grouping together similar segments. Stochastic segmentation is first used to segment the continuous demonstration into movement primitives. The proposed system is tested and demonstrated on an experimental data set consisting of exercise data performed by a long distance runner over the course of training for a marathon. Chapter 2 summarizes the motion representation and abstraction approach, Chapter 3 describes the experimental protocol, Chapter 4 outlines the experimental results, and Chapter 5 concludes the paper and provides directions for future work.

II. MOTION REPRESENTATION AND ABSTRACTION

A. Motion Representation

A Hidden Markov Model (HMM) abstracts the modeled data as stochastic dynamic process. The dynamics of the process are modeled by a hidden discrete state variable, which varies according to a stochastic state transition model $A[N, N]$, where N is the number of states in the model. Each state value is associated with a continuous output distribution model $B[N, K]$, where K is the number of outputs. Typically, for continuous data, a Gaussian or a mixture of Gaussians output observation model is used. HMMs are commonly used for encoding and abstracting noisy time series data, such as speech [13] and human

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motion patterns [14], [15]. Efficient algorithms have been developed for model training (the Baum-Welch algorithm), pattern recognition (the forward algorithm) and hidden state sequence estimation (the Viterbi algorithm) [13].

A Factorial Hidden Markov Model (FHMM) [9] is a generalization of the HMM model, where there may be multiple dynamic processes interacting to generate a single output. In an FHMM, multiple independent dynamic chains contribute to the observed output. Each dynamic chain m is represented by its own state transition model $A_m[N_m, N_m]$ and output model $B_m[N_m, K]$, where M is the number of dynamic chains, N_m is the number of states in dynamic chain m, and K is the number of outputs. At each time step, the outputs from all the dynamic chains are summed, and output through an expectation function to produce the observed output. The expectation function is a multivariate Gaussian function with the chain output as the means, and a covariance matrix representing the signal noise.

Once a group of either HMM or FHMM models has been generated, they can be compared by using a probabilistic distance measure [13]:

$$D(\lambda_1, \lambda_2) = \frac{1}{T}[logP(O^{(2)}|\lambda_1) - logP(O^{(2)}|\lambda_2)] \quad (1)$$

where λ_1, λ_2 are two HMM or FHMM models, $O^{(2)}$ is an observation sequence *generated* by λ_2 and T is the length of the observation sequence. Since this measure is not symmetric, the average of the two intra HMM distances is used to form a symmetric measure. The distance measure is based on the relative log likelihood that a generated sequence is generated by one model, as compared to a second model. It represents a Kullback-Leibler (KL) distance between the two models. The distance measure quantifies the level of difficulty in discriminating between two models λ_1, λ_2.

B. On line segmentation and clustering approach

In the proposed approach [11], [16], the on-line learning system autonomously segments, clusters and learns the sequencing of full-body motion primitives from on-line observation of full body human motions. First, the incoming continuous time series data is segmented into potential motion primitive segments. The Kohlmorgen and Lemm segmentation algorithm [17], [18] is used to perform the segmentation. This algorithm finds optimal segment points by defining a Hidden Markov Model over a set of sliding windows defined over recently observed data. A state transition model is defined such that the cost is lowest to remain in the same state (i.e, there is an increased cost to switch states), and an observation function based on the difference between the current data and the data in the state window. The optimal sequence of segments is found by formulating an optimization based on the tradeoff between data similarity and the cost of switching to a new state. The optimization problem is solved via an online version of the Viterbi algorithm.

Once the incoming time series data has been segmented into potential primitives, each segment is sequentially passed to the clustering module. In the proposed clustering approach [19], [20], a hierarchical tree structure is incrementally formed representing the motions learned by the system. Each node in the tree represents a motion primitive, which can be used to recognize a similar motion, and also to generate a model of the motion. Within each local area of the motion space, a standard clustering technique [21] is used to subdivide motion primitives, based on the Kullback-Leibler distance between motions.

The algorithm initially begins with one group (the root node). Each time a motion is observed from the teacher, it is encoded into an FHMM and compared to existing groups via a tree search algorithm, and placed into the closest group. Each time a group is modified, local clustering is performed within the exemplars of the group. If a a cluster with sufficiently similar data is found, a child group is formed with this data subset. Therefore the algorithm incrementally learns and organizes the motion primitive space, based on the observations received thus far.

III. Experimental Procedure

The data used to validate the proposed approach was collected during the course of a marathon training program. The subject, a 33 year old female, undertook the Stanton marathon training program in preparation for the 2009 Tokyo Marathon. The training consists of a 16 week program, with a 5-day a week running schedule which gradually increases the running distance covered from 20km per week in the first week, to a maximum of 80km per week in the peak 13th week, before tapering in the final 3 weeks before the race. A summary of the training program weekly distances is shown in Table I. Prior to the start of the marathon training, the subject was running on average 25km per week.

During the course of the training, the subject was recorded once a week in the motion capture studio. On several weeks over the course of the training program, recording sessions were omitted due to the lack of availability of the subject or the motion capture studio. The recording dates are indicated in Table I. During each recording session, the subject performed leg exercises consisting of squats and right and left leg lunges. Figure 1 shows extracted frames from video of the recording session. The subject performed 10 repetitions of each exercise during each recording session. Leg exercises were selected as the ones most likely to show changes in movement quality over the course of this type of training.

The motion was recorded in a motion capture studio using the Motion Analysis motion capture system. A set of 35 markers were attached to the body of the subject.The marker positions were captured by a set of 10 cameras at a sampling rate of 5ms. The marker data was then converted to joint angle data using on-line inverse kinematics [22]. A 34 degree of freedom kinematic model of the human body was used to obtain the joint angle data. The kinematic model consists of spherical joints at each shoulder, wrist, hip, and ankle, rotational joints at each elbow and knee, a spherical joint representing the upper torso, a spherical

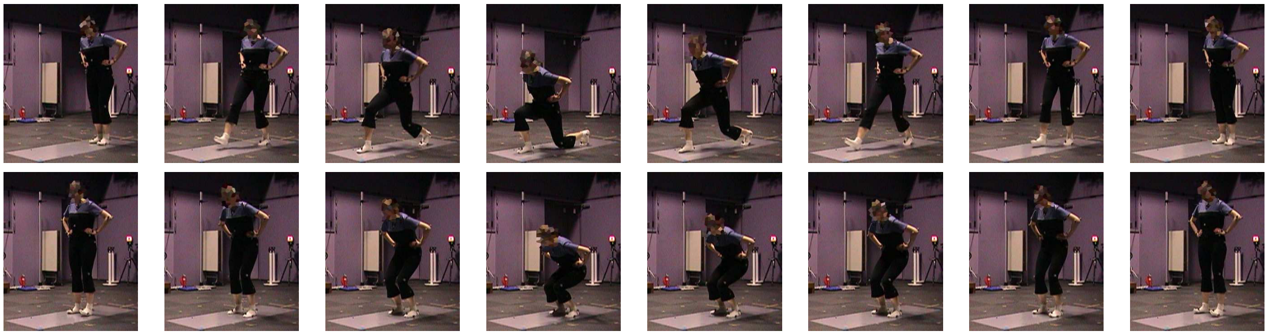

Fig. 1. Sample Motions from the data set.

TABLE I
TRAINING AND RECORDING SCHEDULE SUMMARY

Week	Weekly Dist. [km]	Recorded	Notes
0	25	Y	
1	38	N	
2	38	N	
3	43	N	
4	43	Y	
5	46	Y	
6	46	N	
7	49	N	Start of Strength Training
8	54	Y	
9	0	N	Subject missed training week due to illness
10	50	Y	
11	62	Y	
12	62	Y	
13	67	Y	
14	53	Y	
15	62	Y	
16	67	Y	
17	53	Y	
18	25	N	

joint representing the neck, and a 6DoF free body joint representing the position and orientation of the body in the global reference frame. The joint angle data was then used for subsequent analysis. Since the motions being considered consisted of leg motions only, only the hip, knee, and ankle data were used for the analysis.

IV. Experiments and Data Analysis

The data set was first analyzed to confirm that this type of motion representation can distinguish between gradual movement changes that occur during sports training. This was done by manually clustering the data based on the recording date and analyzing the distances between clusters to determine if an observable pattern could be detected. The recorded data was first segmented using the stochastic segmentation approach described in Section II. The generated segments were inspected and manually labeled. The segments were then grouped together by collection date, and an FHMM motion model was formed for each session and motion type. Each FHMM consisted of 2 chains of 8 states each. Distances were then computed between each session models for each motion type, to determine if FHMM motion modeling and Kullback-Liebler distances can be used to detect changes in the movement.

During the early weeks of training, when the training distance is increasing slowly, no significant differences are detected. However, in the final 5 weeks of training, when the training becomes more intense, differences become clearly observable. Figure 2 shows the distance measures for the squat lower motion and squat raise motions, starting from Week 13 of training. For both motions, each week's model is becoming increasingly different from the baseline motion (at Week 13).

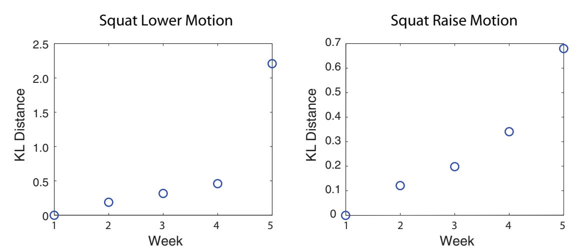

Fig. 2. Kullback-Liebler Distances for the squat motions

Next, the data is analyzed through the automated segmentation and clustering system. Figure 3 shows the resulting final tree structure, after all the data are sequentially presented to the algorithm. The node number on each node indicates the node formation order. Initially, following the data from the first recording session, the 6 motion types are easily extracted (nodes 1 to 6). During the first 10 weeks of data collection, small changes only are observed, such that the subsequent data is grouped into the existing 6 nodes, but no further sub-clustering takes place. After week 12, larger changes in the motion primitives occur, resulting in new nodes being formed in the database, as child nodes of the original nodes (nodes 7 - 18). The squat raise motion undergoes the most change, resulting in three sub-nodes. The formation of subnodes indicates that new motions observed after week 12 are significantly more similar to each other than to motions observed earlier in the training set, i.e., that the motion has undergone larger changes. From a visual inspection of the motions, it appears that the later motions are deeper (i.e., further lowering of the torso) than earlier motions.

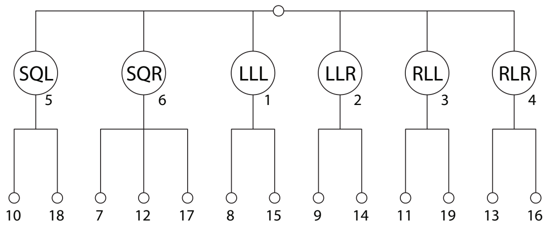

Fig. 3. Resulting Tree for Automatic Clustering. SQL = Squat Lower, SQR= Squat Raise, LLL = Left Lunge Lower, LLR = Left Lunge Raise, RLL = Right Lunge Lower, RLR = Right Lunge Raise. Note that the algorithm clusters only on the basis of K-L divergence, the node labels are generated manually for visualization. The node number indicate the order of node formation.

These results indicate that the proposed fully automated algorithm can be utilized to automatically detect when changes in the quality of motion are occurring, as indicated by the formation of new nodes. The proposed approach is flexible as it requires no a-priori specification of the type or number of motions to analyze; these are abstracted automatically from the movement data itself. This feature would be very useful for a broad range of applications such as rehabilitation or sports training, where the type of motion used may be very variable based on the capabilities of the subject and/or the type of activity being analyzed.

V. Conclusions and Directions for Future Work

This paper proposed an approach for detecting the gradual change in the quality of motion via the use of stochastic modeling of joint angle time series data. An automated approach for extracting and clustering the movement primitives was also applied. The approach was tested on a human movement dataset obtained during a four month marathon training regime for a single subject. Abstracted motions clustered during the early part of the training can be clearly differentiated from later motions via the Kullback-Liebler distance between models, indicating that, with the use of stochastical modeling, it is possible to automatically detect incremental changes to human motion. These results indicate that the approach shows promise for use in automated movement analysis, with potential applications to rehabilitation, sports training and medical diagnosis.

Future work will focus on validating the proposed method on a larger number of subjects, as well as implementing an integrated analysis system by combining the automated results with input from the analyst.

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