A Signal-Shift Boosted Hidden Markov Model for Plyometric Training

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Abstract- Augmented feedback of relevant training parameters is of great interest for athletes and coaches. In plyometric training, the ground contact time and the airtime were identified as crucial measures to monitor and optimize training. This paper introduces a method to determine these parameters with Inertial Measurement Unit measurements and a Hidden Markov Model analysis. To increase the jump phase detection performance, a signal-shift boosting method based on the enhancement of the observation vector was implemented and evaluated on a dataset of eight subjects. Our algorithm achieved an absolute ground contact time error of 12.3 ms and an absolute airtime error of 14.3 ms over all 80 jumps that were collected. The proposed measurement setup and analysis algorithm can be used to create a wearable augmented feedback system for plyometric training practice.

inertial measurement unit; hidden markov model; ground contact time; plyometric training

1. INTRODUCTION

In the sports field, trainers constantly work on optimizing the performance of their athletes. Thereby, it is important to monitor the physical fitness and the training progress. This information is used to decide for the most effective training program according to the athlete level and demands of the particular discipline. Mobile wearable systems can provide the basis of the desired augmented feedback for coaches and athletes, and are therefore a valuable tool to enhance the training effectiveness outside of a lab situation.

Augmented feedback is of great interest if training parameters are difficult to monitor or if small deviations from these parameters substantially change the training effects. This is e.g. the case in plyometric exercises that train reactive strength. The effectiveness of these exercises is determined by the characteristics of the muscle stretch-shortening cycle (SSC). The SSC is thereby influenced by the elastic energy storage of a muscle as well as the activity of the stretch reflex and the Golgi-tendon reflex. The length of the SSC determines the biomechanics of the movement and subsequently the training effects for the athlete. The SSC can be categorized in fast (< 250 ms) and slow (> 250 ms), where the training of a fast SSC is e.g. beneficial for sprinting movements and the training of a slow SSC is e.g. beneficial for maximal vertical jumps [1]. Due to the short length and sensitivity of this parameter, its precise and objective measurement is a valuable augmented feedback parameter.

In literature, the SSC of the plyometric drop jump exercise was often investigated. This exercise consists of a drop from an elevated box or platform and a subsequent vertical jump. The jump is performed as fast and as high as possible and its SSC length coincides with the ground contact time (GCT) of the jump. It has been reported that one effect of plyometric training is a shortening of the drop jump GCT [2]. Furthermore, it has been found that the GCT has the largest effect on important biomechanical jump parameters [3]. Another application of the GCT is the computation of the reactive strength index (RSI), a measure to optimize and monitor plyometric training [1].

Up to date, the GCT of a drop jump is mainly determined by the analysis of the underlying ground reaction forces. Therefore, a force plate or contact mat is needed and data are analyzed offline after the training or recording session. Attempts have been made to compute the GCT and subsequently the RSI with inertial measurement units (IMU) using the root mean square of an accelerometer signal [4]. The authors underlined that the wearable nature and wireless data transmission capabilities of IMU systems enable mobile applications for training practice. However, the generic determination of the take-off proved to be difficult and the processing was performed in an offline manner.

This paper presents a more advanced method to compute the temporal parameters of the drop jump exercise using kinematic IMU data. The analysis is based on a boosted Hidden Markov Model and is capable of computing the GCT as well as the airtime of a drop jump. The wireless sensor platform in conjunction with the java implementation of the analysis algorithm is the basis for a mobile and real-time implementation of the system for training practice.

2. MATERIAL AND METHODS

Data collection

We recruited eight male subjects (age [years] 24.4 ± 2.3, height [cm] 185.4 ± 6.5, weight [kg] 83.5 ± 8.2) for data collection. They were trained athletes and had prior experience in plyometric training exercises. A minimum of 50 cm jump height in a Jump and Reach Test was the criterion to participate in the study. The data collection was conducted in a gymnasium in the sports center of Erlangen University.

Subjects were equipped with instrumented sports shoes. A Shimmer^{TM} 2R IMU (Shimmer, Dublin, Ireland) [5] was mounted on the heel (lateral) of each shoe using a sensor clip. The sensor node comprised of a 3-D accelerometer (range ± 6 g) and a 3-D gyroscope (range ± 500 °/s). Data were sampled with 512 Hz and wirelessly transmitted to a recording PC. As reference, a Casio EX-FC100 high-speed camera (Casio, Tokio, Japan) recorded the experiment with a frame rate of 1000 fps. Both sensors and the video recording were synchronized with a specific movement pattern in front of the camera.

The protocol of the study consisted of a warm-up phase, five drop jumps as well as other plyometric exercises (not used here) and a cool down phase. The subjects used a drop height of 30 cm and had to walk back to the drop platform to perform the next jump. Overall, eight experiments were recorded that incorporated two sensor recordings of five drop jumps. We used 80 labeled drop jumps for further analysis.

The resulting data of the right and the left shoe were transformed to the same coordinate system to be able to process both sides with the same data analysis algorithm. We adapted the signs of the accelerometer axis in the transversal plane to account for the different lateral movement directions of the right and the left foot. We also adapted the corresponding gyroscope axes to harmonize supination and pronation movements of the right and the left foot. Data packets lost during wireless transmission were detected by inspecting the timestamps and data were linearly interpolated.

Data analysis overview

Our analysis processed the complete sequence of five drop jumps that also incorporated steps and miscellaneous movements during data collection. It consisted of three steps:

1. **Data segmentation**: Trigger event to find a drop jump movement candidate. We used the ankle rotation in the sagittal plane as movement pattern to trigger the drop jump analysis. Values up to the maximum range of the IMU were discovered at the beginning of the impact of the drop jump. We manually set the segmentation threshold to ± 500 °/s and the beginning of the analysis window was set 20 samples (39.1 ms) prior to the threshold.
2. **Pattern analysis**: Fine grain analysis of the candidate movement pattern. We used a Hidden Markov Model to determine the different phases of the drop jump. A static pattern length of 550 samples (~1.1 s) was analyzed. The algorithm is described in more detail below.
3. **Post processing**: Elimination of misdetections. We assumed a minimum ground contact time of 100 ms (52 frames) and regarded all patterns with a lower value as misdetection.

Pattern analysis with Hidden Markov Model (HMM)

We used a HMM [6] to analyze the candidate movement patterns in more detail and determine the ground contact time and airtime of a drop jump. HMMs are a popular methodology to analyze sequential data and have been successfully used to classify kinematic IMU data in the field of sports [7]. This technique combines the information of an observation (e.g. IMU signal) with the sequence information (system state). Thereby, the transition to the next state depends on the current observation and the current state (Markov property). Two underlying stochastic processes are considered: The relation of an observation to its corresponding model state (observation distribution) and the relation of two subsequent model states (state transitions distribution). A HMM is defined as $\lambda = (A, B, \Pi)$ with A being the state transition distribution matrix and B being the observation distribution information. The probability of each state being the initial state of the sequence is encoded in the vector Π.

We trained the analysis models with labeled drop jump sequences and the Baum-Welch algorithm [6]. This algorithm adjusted the parameters of the model λ according to the training data. The observation distributions were modeled as multivariate Gaussians. In the working phase, sequences were analyzed for their most probable state sequence according to a trained model. We used the Viterbi algorithm [6] to analyze the test sequences.

We modeled a drop jump as a HMM with six states (Fig. 1). The segmentation was based on the reference video and visual inspection of the data (Fig. 2). It was partitioned to optimally reflect the different data characteristics and to encode the parameters of interest. The GCT comprised the impact phase and the take-off phase and the airtime phase coincided with the flight phase. Thus, the lengths of the resulting phases were used to compute the ground contact time and airtime in milliseconds.

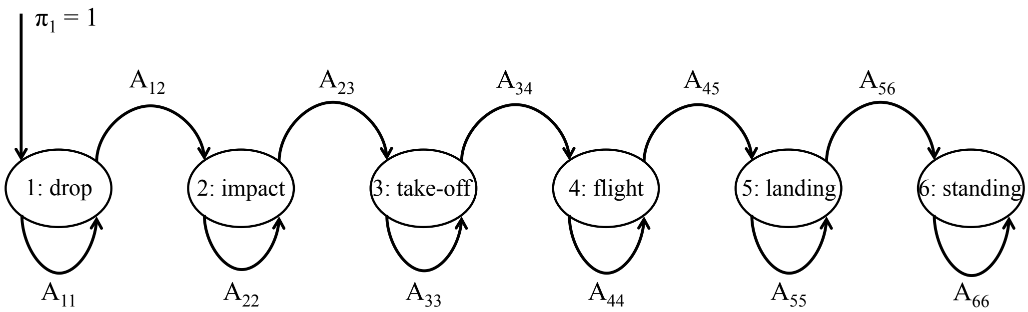

Figure 1. Left-right state transitions of the HMM that was used to analyze a drop jump sequence.

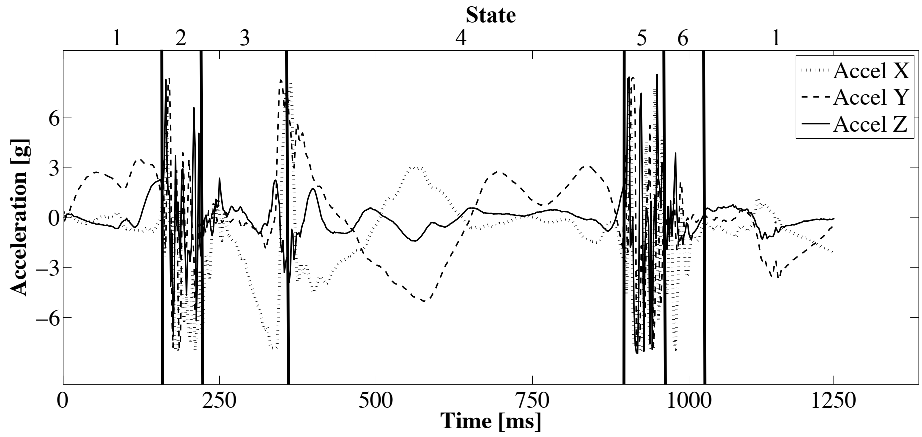

Figure 2. Left foot accelerometer signal of one drop jump and corresponding state segmentation.

Signal-shift boosting

Boosting, the enhancement of the HMM signal space to increase analysis performance, has been successfully implemented for IMU data analysis [7]. The idea of our approach was to enhance the IMU raw data input space with additional time and frequency information. We generated the additional frequency information by filtering the IMU data with a low-pass Butterworth filter (order: 2, cut-off: 15 Hz). The additional temporal information was obtained by maintaining, removing or reverting the delay in the filtered signal. If the delay was reverted, we delayed the raw IMU signal instead of the filtered signal. The delay was estimated as described in [9] and had a value of 15 frames (29.3 ms).

We ran different experiments to assess the influence of additional time or frequency information on the analysis performance:

A. No Boosting: Raw IMU data; 6-D
B. Boosting: Accelerometer and gyroscope; removed filter delay; 12-D
C. Boosting: Accelerometer; removed and maintained filter delay; 12-D
D. Boosting: Gyroscope; removed and maintained filter delay; 12-D
E. Boosting: Accelerometer; removed, maintained, reverted filter delay; 15-D
F. Boosting: Accelerometer and gyroscope; removed, maintained, reverted filter delay; 24-D

Implementation and evaluation

The analysis was implemented in Java using the Jahmm library [8] that provided an implementation of the HMM algorithms. All experiments were conducted with a leave-subject-out cross-validation. In this procedure, the data of one subject were used as test set and the data of the remaining subjects were used to train the model. This procedure was repeated for every subject.

We used five measures to compare the performance. These were the absolute and the mean error of the automatically computed ground contact time and airtime, and the number of misdetections. The reference values were subtracted from the HMM results. Thus, a positive mean error resulted from a longer computed time compared to the reference time. Misdetected drop jumps were excluded from further analysis.

3. RESULTS

The experimental results are compiled in Tab. 1. All 80 drop jumps were successfully detected in every experiment. Experiment C showed the best results for the absolute GCT error and absolute airtime error. The mean GCT error was positive in all experiments and five out of six experiments showed a negative mean airtime error. Experiments C, E and F showed a single or no misdetections.

Table 1. Experimental results of the drop jump analysis. Results were averaged over all jumps. Positive mean error values reflect longer HMM phases compared to reference video.

Exp.	Absolute error GCT [ms]	Mean error GCT [ms]	Absolute error airtime [ms]	Mean error airtime [ms]	Misdetections
A	45.3	44.7	46.6	-45.3	19
B	37.9	37.5	55.2	-20.0	9
C	12.3	10.6	14.3	-12.8	1
D	19.1	18.7	25.6	-8.7	7
E	14.8	13.5	24.8	-24.4	0
F	15.7	13.1	49.0	-3.8	0

4. DISCUSSION

The results of experiment C achieved the best values in the absolute error (GCT, airtime) among all boosting strategies. Thus, the detection of HMM states and therefore jump phases performed best in this experiment. As only one miscellaneous movement was detected as a jump, the HMM was also able to distinguish between drop jumps and other movements like walking or stepping on a platform. Depending on the application, the absolute error values of 12.3 ms and 14.3 ms might be too high for training monitoring and optimization.

The positive values for the mean GCT error showed that this value was mostly overestimated. In contrast, the negative values for the mean airtime error showed that this value was mostly underestimated. As the ground contact and flight were neighboring phases, the error most probably originates in the detection of the take-off. This coincides with the findings in [4].

The signal-shift boosting of the HMM considerably improved the estimation of the essential drop jump parameters. For the purpose of drop jump temporal phase estimation the filtered accelerometer signal with removed and maintained filter delay performed best. This, of course, might not be the case for other applications. Consequently, filter parameters, shift intervals and axes need further investigation. A further option for further studies is to fuse the information from both feet in the case of two-legged jumps.

The system we introduced can be used to estimate the crucial drop jump parameters ground contact time and airtime with shoe-mounted IMUs and a HMM analysis. Improved results were achieved with a signal-shift boosting of the HMM. It is planned to transfer the implementation to a mobile Android™ device to create a mobile augmented feedback application for athletes and coaches.

5. ACKNOWLEDGMENT

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