Comparison of a threshold and a DTW based algorithm for automatic jump segmentation

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Abstract- The evaluation of vertical jumps is an established method in sports performance and medical diagnostics. To simplify data analysis such jumping series need to be segmented automatically. In the present study, we investigated two algorithms (threshold based; dynamic time warping based) regarding their performance to segment vertical jumps on the basis of biomechanical data. Data from 9 subjects was acquired in a motion capture laboratory using 8 infrared cameras and 2 force plates. The data was manually annotated (reference data). Algorithm parameter optimization was then performed to minimize misdetections as well as detection time differences between gold standard and automatic segmentation. The threshold based algorithm correctly detected all jump trials, while the dynamic time warping approach showed lower detection rates with a higher temporal deviation of the determined jump's start and end points. The threshold based approach may be used as a reference algorithm in the evaluation of other segmentation algorithms.

Keywords- Biomechanics; Jump Segmentation; Dynamic Time Warping

1. INTRODUCTION

Vertical jumps such as counter movement jumps (CMJ), squat jumps (SJ) or drop jumps (DJ) are established tools for the evaluation of jumping performance [1,2,3]. The evaluation results play an important role not only in enhancing performance in professional sports, but also in clinical diagnostics for providing information about joint and muscular pathologies and for prevention [4,5,6,7]. A standard evaluation method is the analysis of ground contact and flight times and the calculation of jump performance parameters [8]. Furthermore, modern motion laboratories allow for the investigation of kinematic and kinetic biomechanical parameters such as joint angle, moment and power curves. For the efficient analysis of a high number of trials and the incorporation in sports medical diagnostic routines, manual segmentation might not be an option due to time limitations and the need for repeatable and robust analyses. Therefore, automatic segmentation algorithms are required.

In this work, two automatic segmentation algorithms are compared. The first algorithm is threshold based and represents a simple approach. The second algorithm uses template based segmentation. When using a template based approach, nonlinear matching is needed, because jumps are usually non-periodic motions and high inter subject temporal differences exist. Different matching algorithms exist [9] and in this work we chose dynamic time warping (DTW) [10]. As we use multiple biomechanical parameters and want to detect subsequences similar to predefined templates, multidimensional subsequence DTW [11] was applied on the jumping data.

A standard method to determine ground contact times in jumping performance evaluation is the usage of force plates [12] or optical systems (such as OptoJump, Microgate, Bolzano, Italy). The obtained results are further used to deduce other important parameters such as acceleration, velocity and power output in vertical jumps [8,12]. Nevertheless, they cannot be used for a biomechanical and neurophysiological analysis and they provide no information about other sub phases of a jump. The results from a preceding segmentation can be used to obtain information of all jump phases and to extract relevant jump parameters. As subsequence DTW has already been successfully applied on gait signals with length variations [13], it is now applied on vertical jumps. For the used jump types, evaluation results for neither threshold based algorithms nor DTW have been found.

The purpose of this work is therefore to compare the performance of a threshold based segmentation algorithm and a multidimensional subsequence DTW algorithm applied on biomechanical data for three common jump types (CMJ, SJ, DJ). An application of an automatic segmentation is a fast data analysis with repeatable and comparable results on extensive jump trial series.

2. MATERIAL AND METHODS

Data acquisition

Nine healthy subjects volunteered for this study and gave written informed consent (3 females, 6 males; age 23.2 ± 1.5 yrs; weight 69 ± 9 kg; height 177 ± 7 cm [mean ± SD]). The study was approved by the ethics committee of the University Erlangen-Nuremberg (Re.-No. 106_13 B). Neither of the subjects performed a jumping related sport nor was familiar with functional testing using vertical jumps.

Data collection took place in a biomechanical laboratory consisting of 8 Qualisys infrared cameras (Qualisys, Gothenburg, Sweden) and a split belt fully instrumented treadmill (Bertec, Columbus, OH, USA), which was used to collect force data for both feet separately. Kinematic data was sampled at 200 Hz frame rate, the force data at 1000 Hz. Both modalities were acquired in QTM 2.8 (Qualisys) using camera frame wise synchronization. 38 passive markers were attached to unique anatomical landmarks (6 degrees of freedom marker set including clusters and Visual3D pelvis definition) of the lower body for computation of the static biomechanical model and 32 markers were used for angular calculation using Visual3D (C-Motion, Germantown, MD, USA). Left and right ankle, knee and hip angles as well as pelvic angles and position (relative to the laboratory coordinate system) were calculated using 6 degrees of freedom.

The subjects started with a 5 minute warm up on a cycling ergometer at 80 W in order to reduce the risk of injury and to increase neuromuscular motivation. Afterwards, a jump-and-reach-test was performed to quantify the subjects' jumping performance (mean height 41 ± 8 cm). The jump types were explained and demonstrated to the subjects before each series. The subjects were allowed two test jumps per type for training purposes. They executed each jump at least eight times. They started with DJ (elevated position height of 40 cm), as this jump type aims at the reactive capabilities and is most challenging. The jump type CMJ followed. The last jump series consisted of SJ (squat position duration 1s), as this jump type starts from a squat position with a long pre-stretch period. It is therefore not influenced by smaller stretching effects of the former jumping series. The pause duration between each jump type was 10 minutes for a complete recovering from fatigue. The pause between individual jumps for each jump type was 6 s for DJs and 8 s for CMJs and SJs. The pause times were used for resting and to get back into the initial standing position.

Preprocessing

Markers were labeled by one expert rater in QTM and exported to C3D files. Data preprocessing was performed in Visual3D. Cubic spline interpolation filled signal gaps of 100 frames or less. Second order Butterworth low pass filters were applied to the data. A cutoff frequency of 6 Hz was used for marker data, while a 30 Hz cutoff frequency was used for force data to better represent impact dynamics of the jumping movements. Afterwards, the data was exported to Matlab (MathWorks Inc., Natick, USA) for further analysis.

Algorithms

The obtained data was segmented manually based on visual inspection in Visual3D. The start and end points of the segmented jumps were used as a gold standard for evaluation of the two algorithms. The first threshold based segmentation algorithm used biomechanical prior knowledge about the jump sequences. The start of a CMJ was based on a pelvis height threshold 'pelvisThresh' that was below the initial standing height. The end was detected, when the difference of the current pelvis height to the initial pelvis height was below a threshold 'pelvisDev' for at least a half second while the first frame of this window was taken as end point. A SJ was first segmented using the same procedure as for CMJ. Then, a second step in this window was performed: A threshold based on the pelvis height derivative ('pelvisDiffDev') for at least half a second found the beginning of the squatting position which was then taken as the start point of the SJ. For DJ, a threshold on the pelvis height from the elevated stand was set to detect the jump's start point ('pelvisThresh'). A backward search was performed from the next jump's start or the end of the complete series. A jump's end point was found when the two following thresholds were met: the difference of the L_1 norm of the left and right ground reaction vectors was larger than a threshold 'delta' and the rotation of the pelvis was bigger than a certain threshold 'pelvisAngle'. The application of these thresholds on single jumps is shown in Fig 1. We optimized the thresholds of this segmentation algorithm in a leave-one-subject-out grid search regarding the improvement of the mean time deviation of the start and end points of the jumps. The average threshold was then taken for further evaluation.

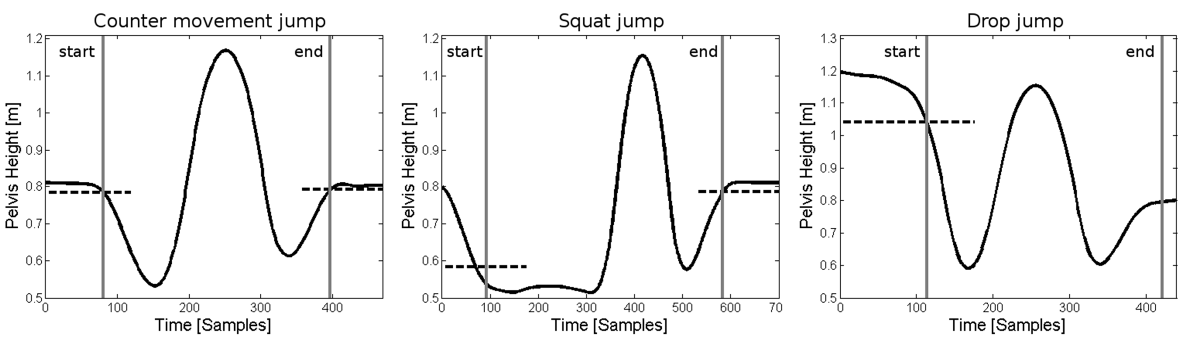

Figure 1. Pelvis height of CMJ, SJ and DJ of representative single jumps. Threshold based segmentation results are indicated by vertical grey lines. The horizontal dashed lines indicate the thresholds on the pelvis height.

For the DTW based segmentation algorithm, templates were created for each biomechanical parameter (= dimension) using the shortest jump that occurred in the training set. We chose biomechanical parameters with regard to their relevance for jumping performance and potential ability to segment the data sets. These parameters were pelvis height, knee, hip flexion angles and vertical ground reaction forces for both knees for CMJ and SJ, and additionally the pelvis rotation angle for DJs. Out of these parameters, subsets were chosen to be evaluated. We normalized each dimension to the [0 1] interval so that parameters of different amplitudes could be used for DTW segmentation. A neighborhood of 1/4 of the template length was ignored in order to avoid overlaps of segmented jumps. The cost threshold τ was optimized in a leave-one-subject-out grid search minimizing the mean time differences and false positives and negatives. For the evaluation results, the individually determined τ were used.

To test the accuracy of the algorithms, the mean time differences (MTD) of start and end points of (correctly) segmented jumps and false positively and false negatively segmented jumps were taken into account. Misdetected jumps were not taken into account for MTD evaluation. The evaluation was performed by a leave-one-subject-out cross validation.

3. RESULTS

The average mean time deviations and false positives and false negatives for both segmentation algorithms are given in Table 1. The threshold based segmentation algorithm segmented all jumps correctly. The averaged parameter grid search results are pelvisThresh=0.97, pelvisDev=0.020 (CMJ); pelvisThresh=0.719, pelvisDev=0.028, pelvisDiffDev=0.0012 (SJ) and pelvisThresh=0.86, Delta=0.52, pelvicAngle=17.9 (DJ). The DTW results in Table 1 are based on pelvis height for CMJ and SJ and on pelvis height and knee flexion angles for DJ. These parameters resulted in the best detection rates and lowest mean time deviations.

Table 1. Results of both segmentation algorithms with false positives (fP) and negatives (fN) and mean time deviation (MTD) of start and end points.

Results	**Threshold based**			**DTW**		
	CMJ	***SJ***	***DJ***	***CMJ***	***SJ***	***DJ***
# jumps	72	73	74	72	73	74
fP / fN	0 / 0	0 / 0	0 / 0	14 / 13	8 / 8	28 /42
MTD [ms]	169 ± 22	300 ± 132	169 ± 88	260 ± 124	534 ± 295	411 ± 78

4. DISCUSSION

The implemented threshold based algorithm is promising for obtaining robust and accurate segmentation results which are not only based on ground contact times but the whole jumping phases. It gave better results than the DTW algorithm. As the jump time series exhibited only slow changes at the beginning and at the end of the jumps, finding the exact time point of start and end of the jump was challenging. Therefore, the mean time deviations were high for both algorithms. These slowly varying parameters might also be the reason for the bad performance of the DTW algorithm with respect to misdetections. A more refined search for start and end points in DTW segmentation or a combination of both algorithms might enhance the results.

In this study, the choice of biomechanical parameters, especially for DTW, contained subjective elements. A further evaluation using an automatic parameter selection could detect parameters that give better segmentation results.

As the subjects were not familiar with functional jumping tests, they gave rise to variability in the data. In effect, the algorithms were tested on heterogeneous data. Therefore, the threshold based algorithm can be regarded as being robust against variations in jump execution. Although the subject population was quite diverse, the algorithms should still be tested on injured patients or subjects with a jump intensive sport background.

A drawback of the threshold based algorithm is that it cannot be applied to other movement forms, as it is based on prior knowledge about the time curves of the biomechanical parameters and threshold selection. DTW is theoretically not limited to the given jump forms but parameters still have to be selected and τ needs to be optimized if new jump forms are introduced.

The threshold based algorithm is not as computationally expensive as the DTW algorithm. It can also be used in a real time approach, even though time delays are introduced due to the backward search in the DJ segmentation. A fast and robust segmentation could allow a direct feedback to the subject or physician.

To summarize, two segmentation algorithms have been evaluated on jumping data. While the DTW approach did not segment the data satisfactory, the threshold based approach gave robust and accurate results for all jumps. It could be used as a new gold standard when testing other segmentation algorithms.

5. References

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