How low can you go?: The use of acceleration data for classifying movement patterns within a data-driven framework

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INTRODUCTION

- We have previously developed a data-driven framework to classify movement patterns using a PCA-based pattern recognition technique and machine learning (Figure 1) [1,2].
- The technique uses full-body motion capture data and is able to classify 82.91% of athletes as elite or novice during a drop-jump task.
- However, motion capture systems are time consuming to set-up and expensive, which reduces their accessibility and feasibility in clinical, ergonomic and sport settings.
- The purpose of this study was to assess how well the developed framework performed with acceleration data, which can be collected easily and inexpensively in the field.

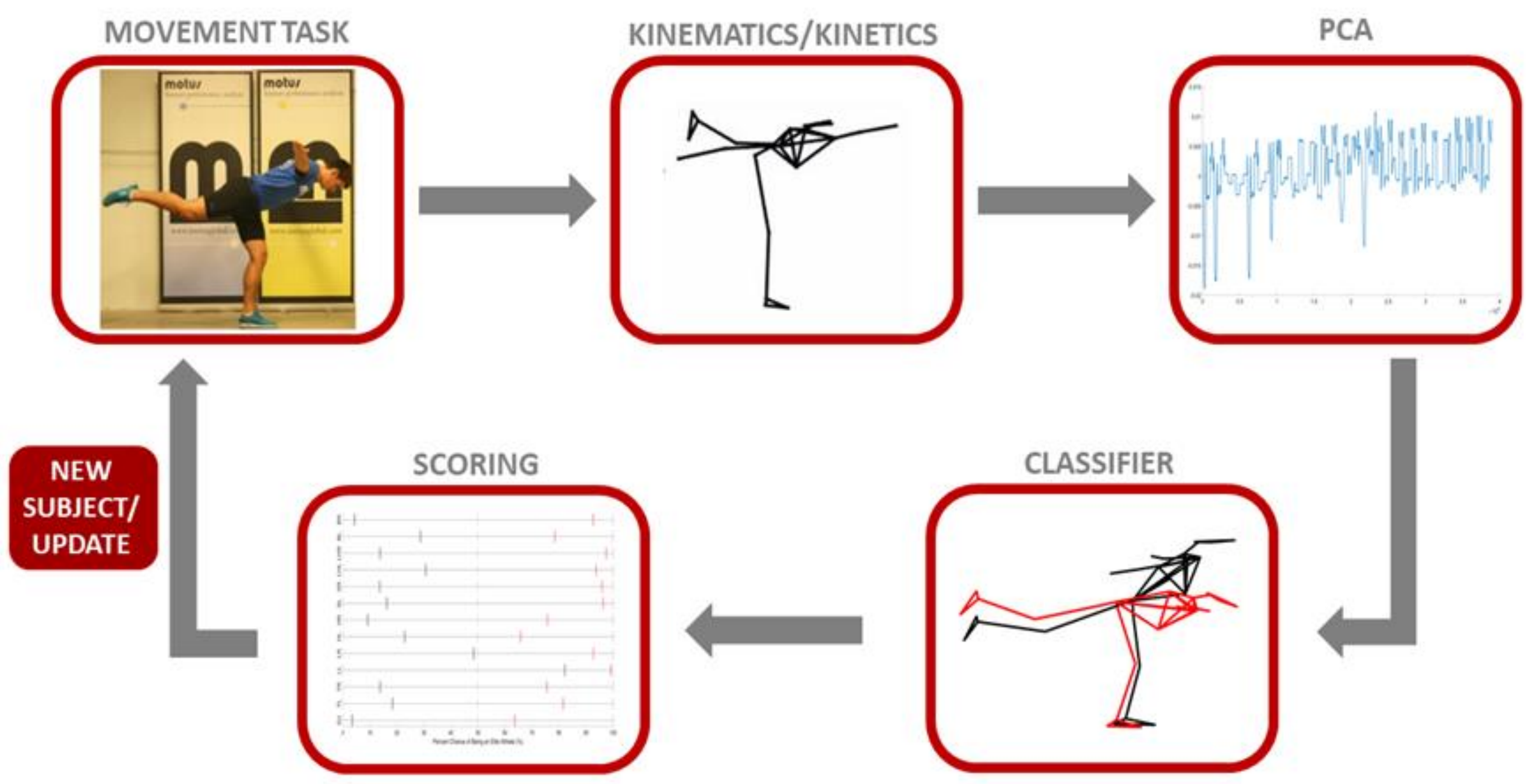

Figure 1. The schematic of the developed framework for classifying movement. The proposed framework consists of five parts: a) a movement task or screen, b) collection and pre-processing of desired kinematic/kinetic data, c) principal component analysis (PCA) to identify key patterns and features, d) machine learning to classify based on chosen criteria, and e) scoring of movement quality.

METHODS

- 3-D motion capture from 270 athletes varying in age and athletic skill (i.e. recreational, youth, high school, college and professional) were collected during a drop jump (Figure 2).
- Motion data were collected using an 8-camera motion capture system (Raptor-E, Motion Analysis, Santa Rosa, CA, USA).
- 26 anatomical markers were used to represent whole-body motion capture.
- Positional data from the 26 makers were trimmed to the initiation of the jump (when the wrist or knee started moving) to the maximum vertical height achieved.
- Data were time-normalized to 500 points and filtered using a lowpass Butterworth filter at 15Hz.
- Data were differentiated twice to calculate acceleration data.

Figure 2. Drop-Jump.

METHODS CONT.

- PCA was used to identify which locations contributed the most amount of variance across all participants during the drop-jump.
- Marker locations were averaged across time and axes and ranked from 1 to 26 in decreasing order from largest to smallest contribution to overall variance (Figure 3).
- The previously developed framework was then applied 26 times, beginning with 3-D accelerations from only one location and adding those from an additional location with each iteration.
  - Linear discriminant analysis was used as the machine learning technique.
  - Skill level (novice vs. elite) was used as the classifier.

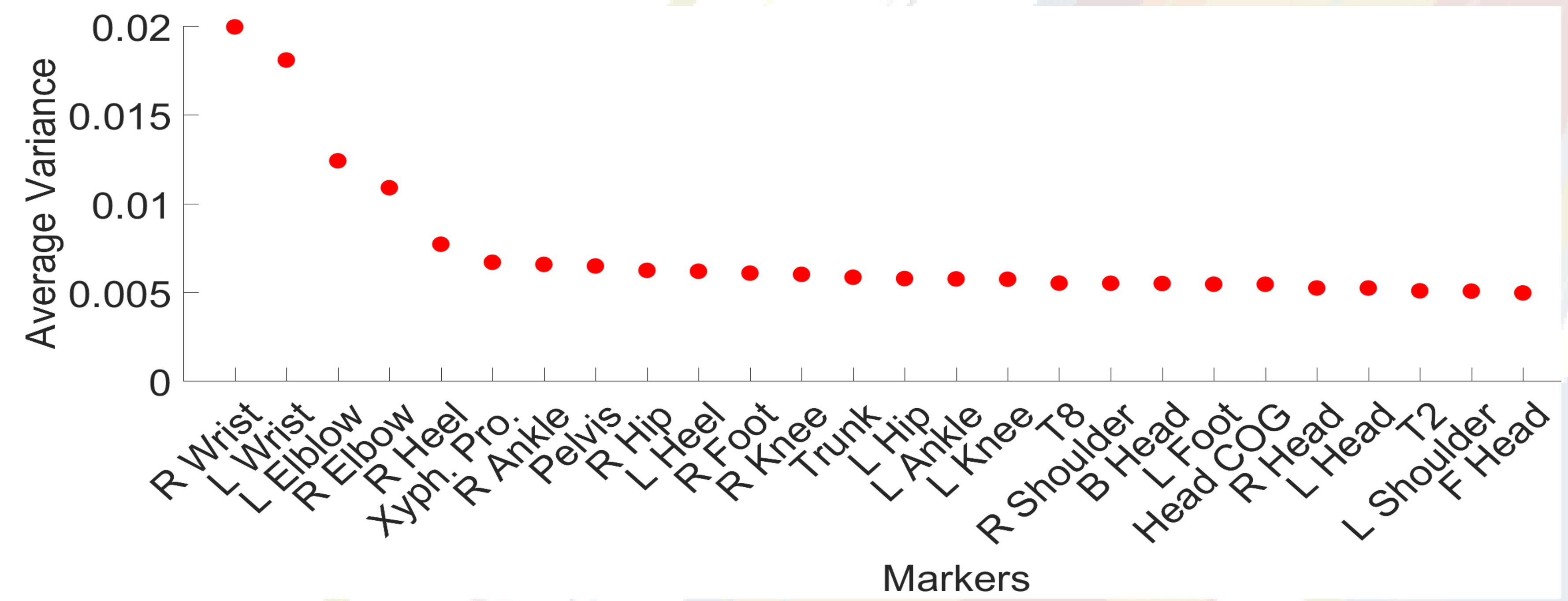

Figure 3. The amount of contributing average variance for each marker in descending order. Values obtained from the PC for each marker were averaged over time. The average value for the x, y and z axes for each marker were then averaged.

RESULTS

- Percentage of correctly classified athletes only increased by 2.91% when keeping data for all markers compared to only 1 marker (Table 1) and only 1.46% when keeping all markers compared to 2 markers (Table 2).

Table 1. The percentage of correctly classified athletes for the validated and non-validated model when retaining 1-10 markers and all 26 markers.

	Number of Markers Retained										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**ALL**
Non-Validated	80.73	80	80.36	80.73	82.55	81.45	82.18	82.55	82.18	81.45	81.09
Validated	74.91	76.36	76.73	76.73	76.36	77.09	76.36	76.72	77.45	78.18	77.82
Marker(s)	Right Wrist	Left Wrist	Left Elbow	Right Elbow	Right Heel	Xyph. Pro.	Right Ankle	Pelvis	Right Hip	Left Heel	All

DISCUSSION

- This study offers proof that accelerations taken from two locations on the body provide enough information to maintain high classification rates using the previously developed data-driven framework.
- This allows the framework to become more accessible to coaches, clinicians and ergonomists.
- Currently, we are analyzing more tasks (i.e., bird-dog, L-hop, step-down, lunge, and T-balance) to determine if these high classification rates are attained with data from only two locations across multiple movements.
- We are also testing the framework with other types of data (e.g. joint angles), machine learning techniques (e.g., nearest neighbors and support vector machines), and classifiers (e.g., healthy vs low-back pain).

REFERENCES & ACKNOWLEDGEMENTS

[1] Ross, G. et al. (2018) Medicine & Science in Sports & Exercise, In Press. [2] Troje, N. (2002). Journal of Vision, 2(5); p. 371-387.

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