OBJECTIVELY DIFFERENTIATING WHOLE-BODY MOVEMENT PATTERNS AND QUALITY IN ATHLETES

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INTRODUCTION

- Movement screens, such as the FMS, are frequently used to identify abnormal movement patterns that may increase risk of injury and/or hinder performance.
- Although there is agreement in the literature that the FMS has high inter-rater reliability for total scores, inter-rater reliability is low for some tasks [1,2].
- Data-driven methods can increase objectivity, remove issues related to inter-rater reliability and offer the potential to detect new and important features that may not be observable by the human eye.
- Applying principal components analysis (PCA) to whole-body motion data may provide an objective data-driven method to identify unique and statistically-important movement patterns [3].
- The purpose of this study was to determine if PCA could detect meaningful differences in athletes' movement patterns when performing a non-sport-specific movement screen.

METHODS

PROCEDURE:

- Kinematic data were collected by Motus Global on 542 athletes ranging in skill level from recreational to professional (NBA, MLB, NFL, etc.).
- Participants performed a 21 movement screening battery; however only 7 movements completed bilaterally were analyzed here:
  - Bird-dog, drop-jump, hop-down, L-hop, lunge, step-down, and T-balance.

ANALYSIS:

- PCA was applied to time-series marker trajectory data for all athletes for each individual movement [3].
- PC scores for each participant on the first 10 PCs for each movement were input into binary logistic regression (BLR) models with leave-one-out validation to classify athletes as novice or elite.
- This model was then used to score movement quality for each individual athlete by inputting their individual scores into the BLR model, and determining their percent likelihood of being an elite athlete.
- Linear discriminant functions (LDF) multiplied by +/- 1 SD were used to reconstruct the data for visual interpretation [3].

RESULTS

- Results varied based on the task and are summarized in Table 1.

Table 1. Number of athletes completing each task (n), perceived explained variance (PEV) and classification rate for each task and all tasks combined.

		Male		Female			
Task	n	Elite	Novice	Elite	Novice	PEV (%)	Correctly Classified Athletes (%)
Bird-Dog Left	380	242	83	12	43	99.24	75.00
Bird-Dog Right	387	244	88	11	44	99.23	72.35
Drop-Jump	275	168	64	7	36	98.37	79.27
Hop-Down Left	396	242	99	10	45	98.89	78.03
Hop-Down Right	396	242	97	11	46	98.77	79.80
L-Hop Left	266	159	67	6	34	98.00	71.05
L-Hop Right	267	160	67	6	34	98.28	75.28
Lunge Left	399	246	97	12	44	97.91	69.17
Lunge Right	401	248	97	12	44	98.04	68.82
Step-Down Left	399	246	98	12	43	99.12	82.96
Step-Down Right	399	247	96	11	45	99.12	82.71
T-Balance Left	392	244	92	11	45	98.81	80.87
T-Balance Right	395	244	94	12	45	98.82	80.00
All Tasks Combined	**189**	**106**	**43**	**11**	**29**	**--**	**87.3**

RESULTS CONTINUED

- Differences between elite and novice athletes were observed when data were reconstructed using the LDF (Figures 1-7), where red represents elite athletes and black represents novices.
- To provide clinical application, athletes' PC scores were input into the binary logistic regression model to create a movement report (Figure 8) describing the likelihood (%) that the athlete was an elite for each task and combined performance across all tasks.

Figure 1. Elite and novice performing the bird-dog task

Figure 2. Elite and novice performing the L-hop task

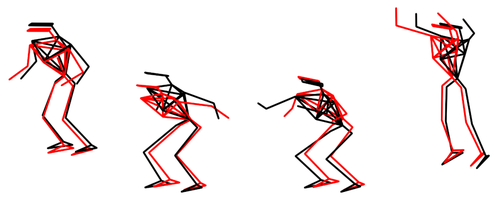

Figure 3. Elite and novice performing the drop-jump task

Figure 4. Elite and novice performing the hop-down task

Figure 5. Elite and novice performing the step-down task

Figure 6. Elite and novice performing the lunge task

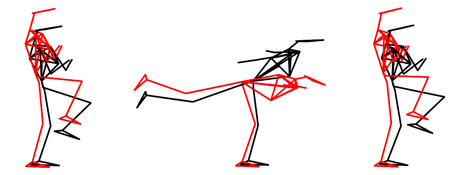

Figure 7. Elite and novice performing the T-balance task

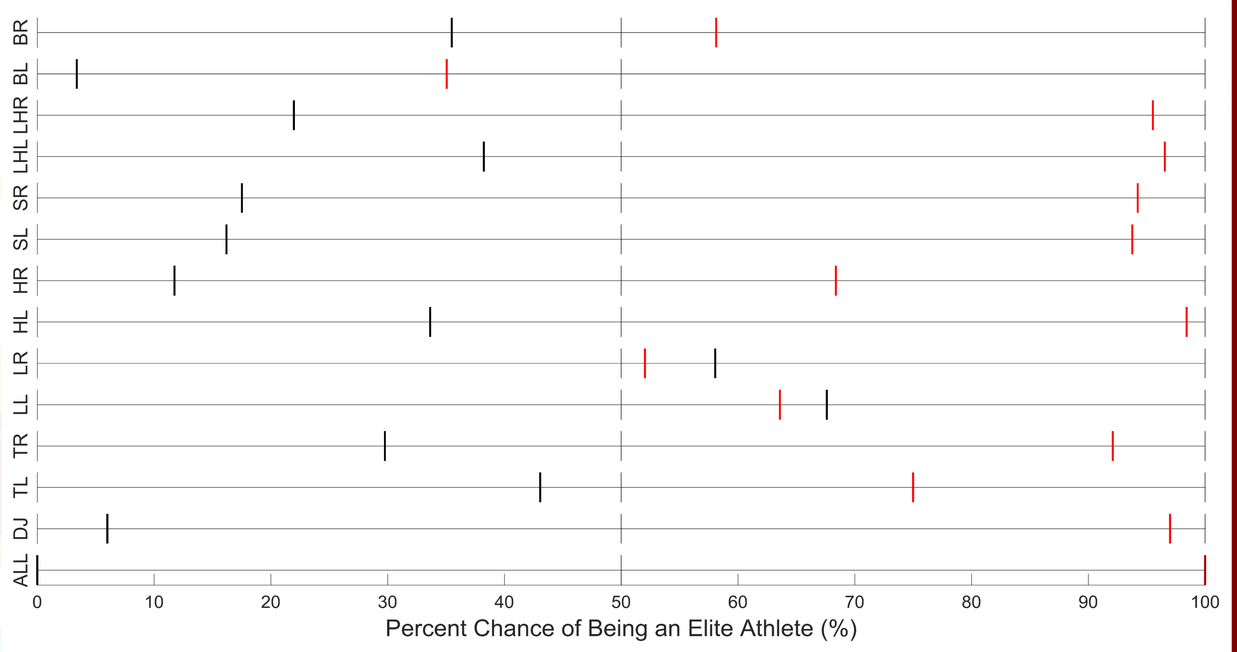

Figure 8. Movement report for an elite basketball player (red) and a novice golfer (black). Created using their individual PC scores for each task and the binary logistic regression models. Lower percentages represent poorer task performance (more novice-like) and a higher percentage represents superior performance (more elite-like)

DISCUSSION

- A novel pattern recognition technique using PCA was able to accurately classify athletes based on level of expertise for both individual movement tasks as well as using a combined movement battery.
- The technique could be used to directly support observational learning to enhance performance and rehabilitation for athletes, increase exercise or program adherence by increasing self-efficacy, and/or be used to create movement reports [4,5].
- Future research should examine other classifiers (e.g. sport played, injury history), the use of inverse and forward dynamics and optimal control models to try to identify common strategies and movements to reduce joint loading and minimize cost functions, and to validate the use of inexpensive motion capture systems.

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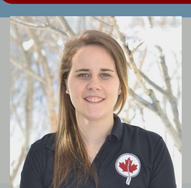

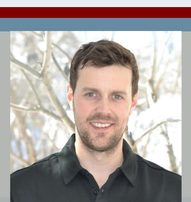

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