OBJECTIVELY DIFFERENTIATING WHOLE-BODY MOVEMENT PATTERNS AND QUALITY IN ATHLETES

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INTRODUCTION
Movement screening tests, such as the Functional Movement Screen™ (FMS), are used to screen for movement abnormalities that may be predictive of performance potential or injury risk in athletes and/or workers [1]. However, these screens are scored subjectively and scores can change based on the rater or the performer’s knowledge of the grading criteria [2]. Quantitative methods can help us understand how underlying attributes (e.g. height, sex, ability, or injury history) contribute to movement patterns. This information can then be used to identify ideal movement patterns for a specific class, facilitating customized movement screening. Using motion capture and principal components analysis (PCA) of whole-body motion may provide an objective data-driven method to identify unique and statistically important movement patterns. Therefore, the purposes of this study were to: 1) examine athletes’ movement variability when performing standardized functional movements using PCA; and, 2) to determine if whole-body movement patterns could be differentiated based on classifiers such as skill level, sport played, injury history, sex, and anthropometry.

METHODS
This study is based on motion capture data collected by Motus Global from 542 athletes representing eight different sports (soccer, baseball, tennis, basketball, lacrosse, track and field, golf, and football) ranging in ability from recreational (e.g. do not play on competitive teams) to professional (e.g. NFL, MLB, FIFA). Each athlete performed 14 range of motion tasks and 7 stability tasks, where the tasks were designed to challenge athletes’ balance, stability, and power. Whole-body motion data were captured using an 8-camera Raptor-E motion capture system (Motion Analysis, CA, USA). PCA was applied to timeseries marker position data for each athlete to reduce the size of the data set for further analysis. The x,y, and z position data for 26 markers were used for the analysis so that whole-body motion patterns could be examined and videos could be created depicting the results for each movement. The PCA outputted the principal components (PC) and corresponding scores explaining individuals’ variance from the mean. Based on pilot data, 10 principal components and scores were retained for both tasks. A linear discriminate function differentiating between skill levels (elite vs novice) was applied to the reconstructed motion data [3]. Data was reconstructed using the equation:

Reconstructed motion = mean movement ± (1 SD*do), [3]

where SD refers to standard deviations and do is the linear discriminate function. To further examine differences between athletes, an ANCOVA was used to determine significant differences in scores between elite and novice athletes. Single component reconstruction was used to interpret the motion each principal component represented [4].

RESULTS AND DISCUSSION
For the purpose of this abstract, only the results from the linear discriminate function for the bird-dog and drop jump will be discussed. However, more tasks and the differences between individual principal components will be discussed in the presentation. For the bird-dog task, the first 10 PCs explain 98.84% of the movement variability and the linear discriminate function accurately classified 77.7% of the cases as either elite or novice athletes. Elite athletes had greater flexion and extension throughout the task and less trunk rotation compared to novice athletes. For the drop jump task, the first 10 PCs explained 97.94% of the movement variability and the linear discriminate function accurately classified 61.3% of the cases. Elite athletes squatted lower during the pre-phase of the jump and reached a greater maximal vertical height compared to the novice athletes. In addition, there are differences between the timing of the arm swing between the two groups. The application of a PCA and linear discriminate function approach provided a data-driven objective method to identify differences in whole-body movement patterns between professional and recreational athletes performing a bird-dog and drop jump task.

CONCLUSIONS
We were able to accurately differentiate between elite and novice athletes using PCA and a linear discriminate function. Future research will look at using other metrics for differentiation such as sport played, injury history, and sex, as well as, interactions between these classifiers. Findings from these classifiers will be discussed in person.

REFERENCES
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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:

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

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

<table>
<thead>
<tr>
<th>Task</th>
<th>Elite</th>
<th>Novice</th>
<th>PEV (%)</th>
<th>Correctly Classified Athletes (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bird-Dog Left</td>
<td>380</td>
<td>242</td>
<td>83</td>
<td>99.24</td>
</tr>
<tr>
<td>Bird-Dog Right</td>
<td>387</td>
<td>244</td>
<td>88</td>
<td>99.23</td>
</tr>
<tr>
<td>Drop-Jump</td>
<td>275</td>
<td>168</td>
<td>67</td>
<td>98.37</td>
</tr>
<tr>
<td>Hop-Down Left</td>
<td>396</td>
<td>242</td>
<td>99</td>
<td>98.89</td>
</tr>
<tr>
<td>Hop-Down Right</td>
<td>396</td>
<td>242</td>
<td>97</td>
<td>98.77</td>
</tr>
<tr>
<td>L-Hop Left</td>
<td>256</td>
<td>159</td>
<td>67</td>
<td>98.00</td>
</tr>
<tr>
<td>L-Hop Right</td>
<td>256</td>
<td>159</td>
<td>67</td>
<td>98.00</td>
</tr>
<tr>
<td>Lunge Right</td>
<td>399</td>
<td>246</td>
<td>97</td>
<td>97.91</td>
</tr>
<tr>
<td>Step-Down Left</td>
<td>399</td>
<td>246</td>
<td>98</td>
<td>99.12</td>
</tr>
<tr>
<td>Step-Down Right</td>
<td>399</td>
<td>247</td>
<td>96</td>
<td>99.12</td>
</tr>
<tr>
<td>T-Balance Left</td>
<td>392</td>
<td>244</td>
<td>92</td>
<td>98.81</td>
</tr>
<tr>
<td>T-Balance Right</td>
<td>395</td>
<td>244</td>
<td>94</td>
<td>98.82</td>
</tr>
<tr>
<td>All Tasks Combined</td>
<td>189</td>
<td>106</td>
<td>43</td>
<td>--</td>
</tr>
</tbody>
</table>

REFERENCES


Figures

- 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.