Objectively Differentiating Movement Patterns between Elite and Novice Athletes

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ABSTRACT

ROSS, G. B., B. DOWLING, N. F. TROJE, S. L. FISCHER, and R. B. GRAHAM. Objectively Differentiating Movement Patterns between Elite and Novice Athletes. *Med. Sci. Sports Exerc.*, Vol. 50, No. 7, pp. 1457–1464, 2018. **Introduction**: Movement screens are frequently used to identify abnormal movement patterns that may increase risk of injury or hinder performance. Abnormal patterns are often detected visually based on the observations of a coach or clinician. Quantitative or data-driven methods can increase objectivity, remove issues related to interrater reliability and offer the potential to detect new and important features that may not be observable by the human eye. Applying principal component analysis (PCA) to whole-body motion data may provide an objective data-driven method to identify unique and statistically important movement patterns, an important first step to objectively characterize optimal patterns or identify abnormalities. Therefore, the primary 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. As a proof of concept, athlete skill level was selected *a priori* as a factor likely to affect movement performance. **Methods**: Motion capture data from 542 athletes performing seven dynamic screening movements (i.e., bird-dog, drop-jump, T-balance, step-down, L-hop, hop-down, and lunge) were analyzed. A PCA-based pattern recognition technique and a linear discriminant analysis with cross-validation were used to determine if skill level could be predicted objectively using whole-body motion data. **Results**: Depending on the movement, the validated linear discriminant analysis models accurately classified 70.66% to 82.91% of athletes as either elite or novice. **Conclusions**: We have provided proof that an objective data-driven method can detect meaningful movement pattern differences during a movement screening battery based on a binary classifier (i.e., skill level in this case). Improving this method can enhance screening, assessment, and rehabilitation in sport, ergonomics, and medicine. **Key Words:** PRINCIPAL COMPONENTS ANALYSIS, PATTERN RECOGNITION, MOVEMENT SCREENING, LINEAR DISCRIMINANT ANALYSIS, CLASSIFICATION, WHOLE-BODY

Movement screens are used to identify aberrant movement patterns believed to increase risk of injury and/or impede performance. Individuals' kinetic and/or kinematic data can be recorded as they perform standardized motions, where those data can be evaluated to determine the correctness and/or proficiency of movement (1–6). However, movement screening is most commonly applied as a visual appraisal of movement (4). Although visual appraisal of movement is useful in terms of coaching, data-driven, quantitative methods could enhance movement screening by increasing objectivity (4,7) and reducing error associated with visual-based appraisal. Data-driven methods may also create the potential to detect new and important movement features that may not be easily visible to the human eye (7). This study explores the viability of a principal component analysis (PCA)–based movement pattern recognition technique as a data-driven approach to objectively characterize movement during a movement screen.

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Movement screens are growing in popularity among practitioners, coaches, and athletes to identify abnormal movements (4,5,8–10). The Functional Movement Screen (FMS™) (Functional Movement Systems, Chatham, VA) offers one example of a movement screen whose use has recently increased in popularity among coaches and trainers and where a number of studies have identified prospective challenges with interrater and intrarater reliabilities (11–15). The FMS™ is a quantitative movement screen in that movements receive a numerical score; however, it is a subjective, quantitative measure because that score is derived based on visual observations by a rater (3,8). Consistent with typical movement screens and the movement screen used in this study, the FMS™ is comprised of movements believed to challenge mobility and stability by requiring participants to move into and out of extreme positions using a self-controlled pace. There is agreement within the literature, that when looking at the overall scores, there is strong interrater and intrarater reliability (11–15) for both novice and experienced raters. However, interrater reliability is poor for some individual movements such as the hurdle step (13,15), as well, the hurdle step has poor intersession reliability (participants were tested on 2 d, separated by a week) (15). In addition, when comparing multiple pairings of novice and experienced raters, only half of the movements (n = 6) had perfect agreement, a quarter of the movements had moderate agreement (n = 3), and a quarter of the movements had slight agreement (n = 3) (11). The poor interrater reliability for some movements is thought to be due to the dynamic nature of the movement(s) (15) and the rater's perspective, where they may only see the performance from one vantage point, making it difficult for the rater to see scoring criteria that are either out of view or occluded by the athlete's body (13,15). A possible solution to address the aforementioned limitations is the use of motion capture.

Motion capture systems are able to objectively track three-dimensional (3D) motions. Motion capture data can be collected to an accuracy of 0.2 mm during static movements and 2 mm during dynamic movements (however, error continues to decrease as technology improves), likely offering greater resolution to detect movement differences compared with visual observation (16,17). Furthermore, 3D motion capture enables the movement to be assessed from multiple vantage points and can be used to collect data to calculate measures that can provide athletes and coaches with quantitative, objective feedback of movement performance (7). However, whole-body 3D motion capture data are extremely high-dimensional, which can be difficult to analyze and interpret. Reducing data to discrete parameters or by applying other data reduction methods, such as PCA can help in analyzing and interpreting motion capture data. The use of PCA for motion analysis, enabling the extraction of fundamental movement patterns, has dramatically increased (7,18–20).

PCA is a multivariate statistical technique that can be applied to reduce the dimensionality of high-dimensional data sets. PCA can reduce dimensionality by identifying redundancies in the data, where a subset of the data will often explain the majority of the variance (20). Although PCA has been applied to joint waveforms (e.g., angles and moments) (21,22), it can also be applied directly to 3D motion capture marker data (20). This allows for whole-body kinematics to be analyzed instead of individual joints, for the data to be reconstructed in a visually meaningful way and to account for body size. As an example, walking can be characterized using motion capture data by describing the 3D positions of multiple reflective markers at each point in time. Applying PCA, an individual's walking pattern can be more efficiently described using the first four principal components (PC), which account for 98% of the total variance in the overarching 3D positional data (20). Using PCA to examine 3D motion capture data (i.e., all marker trajectories) can help accurately identify embedded patterns of complex movements.

The PCA-based movement pattern recognition techniques have been used effectively to detect and explain differences in whole-body movements. For example, differences in gait patterns were detected and explained based on factors including age, body mass index, sex, and feelings (happy/sad, nervous/relaxed) (20,23–25). When applied to ergonomics, egress/ingress motion patterns were detected and explained based on vehicle design (19). In a sport example, PCA was applied objectively to analyze downhill (7) and cross-country skiing (26) technique and to develop an objective judging tool for competitive diving (27). An emerging benefit of this technique is its ability to provide objective biomechanical feedback to coaches and athletes to use when planning training regimens (7). For example, a golf coach can show how a golfer's full body movement patterns and timing of movements during their golf swing compared with that of a professional golfer. However, a less obvious, secondary benefit of the technique is that it can be used to support the development of instructors' or coaches' skills to assess an athlete's movements (7). For example, PCA can identify principal positions/patterns that can be highlighted to coaches, who can then ensure their athletes attain those positions/patterns during practice. The PCA-based movement pattern recognition techniques also allowed researchers to characterize movement features during diving, where dive scores were calculated based on how a given feature pattern related to the mean (27), reducing the inherent variability in traditional observational-based judging. PCA applied to whole-body 3D motion capture data offers researchers, coaches, and judges with a method to objectively assess and even score movement patterns of athletes as they perform their specific movement skills, removing subjectivity/bias from traditional observational-based assessment.

The PCA-based movement pattern recognition approach shows promise, but has not been applied to a movement screen. Objectively classifying athletes' movement patterns based on certain demographics (e.g., height, weight, skill level, sport played, and injury history) could provide a unique data-driven approach to enhance movement screening, training, and rehabilitation. Therefore, the purpose of the current study was to assess the application of a PCA-based pattern recognition technique as a method to differentiate whole-body movement patterns of athletes, using skill level as a dichotomous factor. We chose this factor due to its likelihood to influence movement quality and performance. Further, an example is provided discussing how this data-driven approach could be applied as a coaching tool to inform corrective strategies. Based on previous research, it was hypothesized that a PCA-based movement pattern recognition technique would be able to effectively differentiate between the movements of athletes of different skill levels while performing movements that are not specific to the athletes' particular discipline.

METHODS

Participants

Motion capture data were collected from 542 athletes (Table 1) by Motus Global (Rockville Centre, NY). The sample included athletes competing in baseball, basketball,

TABLE 1. Athletes' mean age, height, and weight broken down by sex and skill level.

	Elite	Novice	Elite and Novice
Male			
n	306	174	480
Age	22.5 (3.5)	16.8 (4.2)	20.05 (4.7)
Height	191.5 (19.8)	174.7 (13.0)	185.3 (19.4)
Weight	95.7 (18.7)	69.7 (18.0)	86.1 (22.3)
Female			
n	12	50	62
Age	23.3 (4.0)	18.0 (5.6)	19.00 (5.7)
Height	170.4 (7.2)	167.0 (8.7)	168.00 (8.9)
Weight	64.3 (8.8)	60.0 (13.7)	61.1 (13.3)
Male and female			
n	318	224	542
Age	22.6 (3.6)	17.1 (4.6)	20.2 (4.7)
Height	190.7 (19.9)	172.9 (12.6)	183.3 (19.3)
Weight	94.5 (19.4)	67.5 (17.6)	83.1 (22.9)

Standard deviations are in brackets.

soccer, golf, tennis, track and field, squash, cricket, lacrosse, football, or volleyball. Athletes' skill level varied from recreational to professional (e.g., NBA, MLB, NFL, PGA, FIFA). Athletes were dichotomized based on skill level (−1, novice; 1, elite) based on the cutoff that elite athletes should have accumulated at least 10,000 h of deliberate practice (28,29). Thus, elite athletes were considered as those competing at the collegiate, semiprofessional, and professional levels, and novice athletes were considered as those competing at all other levels (e.g., high-school, recreational, etc.). Table 1 summarizes the demographics and skill level of participants. Before data collection, each participant read and signed an informed consent form permitting Motus Global to use the data for future research. The Health Sciences Research Ethics Board at Queen's University approved the secondary use of the data for research purposes (file no: 6017208).

Protocol

Upon arrival at the Motus Global laboratory, participants read and signed the consent form. Once the consent form was signed, participants' height (with shoes on) and weight were measured. Athletes were outfitted with 45 passive, reflective markers (B&L Engineering, Santa Ana, CA) placed on specific body locations as required to characterize whole-body motion. Markers (n = 37) were placed on anatomical landmarks, including the spinal process of the second thoracic vertebrae (T_2); the spinal process of the eighth thoracic vertebrae (T_8); xyphoid process; the front, left, right, and back of the head; and, bilaterally on the acromioclavicular joint, sternoclavicular joint, medial and lateral epicondyle of the humerus, ulnar styloid process, radial styloid process, anterior and posterior superior iliac spine, greater trochanter, medial and lateral epicondyle of the femur, medial and lateral malleolus, distal end of the third metatarsal, and calcaneus, as required to describe major body segments (30). Additional tracking markers (n = 8; one marker placed on each thigh, each forearm, each bicep, the right shank, and the right scapula) were applied to assist with tracking the segments and also to aid in differentiating between the left and right sides. Once outfitted with the markers, athletes performed static and dynamic calibration trials. During the static calibration trial, the athlete stood with their feet shoulder width apart and toes pointing straight forward. The arms were abducted 90° with a 90° bend in the elbow. The static calibration was used to align the athlete to the laboratory global coordinate system as well as to define local coordinate systems specific to each athlete. For the dynamic calibration trial, the athlete held the same position as the static calibration trial and then rotated his or her arms 90° both internally and externally.

Each athlete then completed a series of movement tests. The battery consisted of 21 unique movements; however, only seven were used in this analysis including the: bird-dog, drop-jump, T-balance, step-down, L-hop, hop-down, and lunge movement (see Supplemental Digital Content, Figures S1–7, which visually show and provide detailed explanations for each movement, http://links.lww.com/MSS/B210). These seven movements were selected as those most likely to challenge mobility and stability across the shoulder, spine, hip, knee, and ankle joints. With the exception of the bilateral drop jump, all movements were performed on both the right and left sides for a total of 13 motion profiles per athlete. Full-body motion data were captured at 120 Hz using an eight-camera Raptor-E (Motion Analysis, Santa Rosa, CA) motion capture system.

Data Analysis

Preprocessing. Motion capture data were collected, labeled, and gap-filled using Cortex (Motion Analysis). Data from the anatomical landmarks and the tracking markers during the calibration trial were used to develop a 3D, whole-body kinematic model in Visual3D (C-Motion, Inc., Germantown, MD). The model was then applied to all motion trials, outputting three types of positional data: joint centers bilaterally for the wrist, elbow, shoulder, foot, ankle, knee, and hip; centers of gravity for the trunk, head, and pelvis; and, marker positional data for the left and right heel, T_2, T_8, sternum, and the back, front and sides of the head to model the feet, trunk and head more robustly when reconstructing the data. Data were exported to Matlab (The MathWorks, Natick, MA) for further analysis. In Matlab, all trials were clipped to specific start and end-point criteria (see Supplemental Digital Content, Table S1, which outlines the specific start and end criteria for each trial, http://links.lww.com/MSS/B210), filtered using a dual-pass, low-pass Butterworth filter with a cutoff of 15 Hz, and time normalized to 500 frames to control for differences in the absolute movement time.

Application of PCA as a Movement Pattern Recognition Technique

A PCA-based movement pattern recognition technique was used to analyze the data. Using the motion data from each movement, an $n \times m$ matrix was created for each movement; where n represented the number of athletes contributing data, and m represented the time-series motion data for each participant. Noted in Table 2, the number of athletes contributing data to each movement varied as trials were removed from analysis where athletes did not perform

TABLE 2. The number of athletes, percent explained variance, and percentage of correctly classified athletes as either elite or novice using a LDA model with and without leave-one-out validation for each movement.

Movements	n	Male		Female		PEV (%)	Percentage of Correctly Classified Athletes	
		Elite	Novice	Elite	Novice		No Validation (%)	LOO Validation (%)
Bird-dog left	380	242	83	12	43	99.95	77.89	72.63
Bird-dog right	387	244	88	11	44	99.95	80.62	75.97
Drop-jump	275	168	64	7	36	99.91	88.36	82.91
Hop-down left	396	242	99	10	45	99.94	81.31	76.77
Hop-down right	396	242	97	11	46	99.93	80.30	76.26
L-hop left	266	159	67	6	34	99.91	80.83	76.69
L-hop right	267	160	67	6	34	99.91	87.27	80.15
Lunge left	399	246	97	12	44	99.87	81.45	74.69
Lunge right	401	248	97	12	44	99.88	79.55	76.31
Step-down left	399	246	98	12	43	99.95	82.21	78.20
Step-down right	399	247	96	11	45	99.95	81.20	75.94
T-balance left	392	244	92	11	45	99.92	78.57	70.66
T-balance right	395	244	94	12	45	99.93	79.49	73.67

LOO, leave-one-out; PEV, percentage of explained variance.

a particular movement or where marker occlusions did not permit a whole-body representation for the duration of the movement. Time-series motion data were expressed as the x, y, and z positional data for each aforementioned joint center, segment center of gravity, and retained marker (26 positions × 3 axes) for all 500 time points, such that m = 39,000 (23). Separate PCA were applied to the movement data specific to each movement. On average, the sample size for the movement tasks was 365. Using the suggested methodology of 10 participants per predictor in the linear discriminant model (31), the first 35 PC and associated scores for every participant were retained. Since elites were statistically taller than novices (F = 138.25, P < 0.001), all x, y, z positional data for each movement were normalized by each athlete's individual height by dividing each raw data point by their own height. This ensured that differences in PC scores between groups were not strictly due to variation in body size.

Statistical Analysis

Linear discriminant analyses (LDA) with and without leave-one-out cross-validation were used to determine the ability to differentiate athletes based on an athlete's skill level (elite or novice) for each movement individually. For each movement, all 35 PC scores retained from the PCA were used as predictors for the model. Lacking a whole new set of data to test the linear classifier, we ran a leave-out-one validation procedure, where one of the athletes' data were taken out (test athlete) and a linear classifier was computed on the remaining athletes (training athletes). After having done so, the test athlete was projected first onto the PC derived from the training athletes and then the resulting score vector was then projected onto the discriminant function in the subspace spanned by the first 35 components (20). Data were reconstructed such as presented in Figure 1, using the linear discriminant functions for each movement (20). The reconstructed data were calculated using the equation:

$$r = m + \alpha d \quad [1]$$

where r is the reconstructed movement data, m is the mean movement data across all athletes, and d is the linear discriminant function. The scalar variable α is scaled in terms of standard deviations (20), where positive values emphasize features characterizing elites and negative values characterizing novices. As α changes from a negative integer to a positive integer, the reconstructed data are more representative of an elite athlete (20). For visualization purposes (e.g., Fig. 3 and Supplemental Digital Content, Figures S8–14, which show the differences in movement patterns between elite and novice athletes for each movement, http://links.lww.com/MSS/B210), α was set at ±1 to best show differences between the two groups.

Application of the Movement Pattern Recognition Technique

For a practical application of the movement pattern recognition technique, two athletes (one novice and one elite) from the existing database were extracted at random to classify how they scored along the linear discriminant function in terms of Z scores on either side of the mean. Z scores were be calculated by:

$$Z = \frac{X - \mu}{\sigma} \quad [2]$$

where Z is the athlete's Z score, X is the athlete's testing projection (the distance between the athlete's score and the linear discriminant function), μ is the mean testing projection across all athletes, and σ is the standard deviation of the mean testing projection across all athletes. From the Z score, using a normal confidence distribution function with μ equaling 0 and σ equaling 1, the likelihood of being an elite athlete for each movement was calculated. A likelihood of <50% represents more novice-like movements, whereas a likelihood of >50% represents more elite-like movement. An individualized movement report describing the likelihood (percentage) that the athlete was elite for each movement was created.

RESULTS

When 35 PC were retained, the explained variance for each movement was greater than 99.8% (Table 2). The

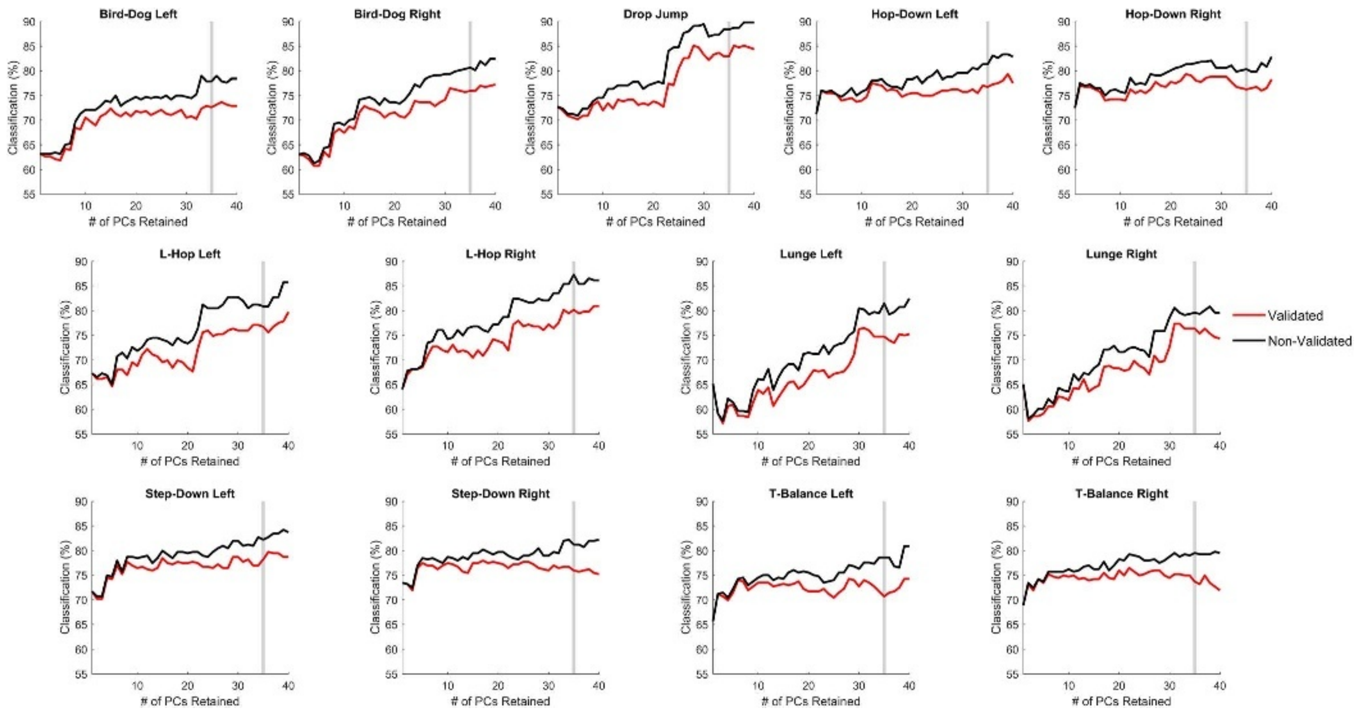

FIGURE 1—The percent of correctly classified athletes for when 1 to 40 PC scores were retained for the LDA models with leave-one-out validation (*red*) and no validation (*black*) for each movement task. The *vertical gray line* represents the number of PC retained for this study (35 PC).

PCA-pattern recognition technique was able to accurately classify between 77.89% (bird-dog left) and 88.36% (drop-jump) of athletes as either elite or novice depending on the movement when not using any validation (Table 2). When leave-one-out validation was used, the PCA pattern recognition technique was able to accurately classify between 70.66% (T-balance left) and 82.91% (drop-jump; Fig. 4) of athletes, depending on the movement (Table 2).

For all tasks, the classification rate (Fig. 1), sensitivity (percent likelihood of an elite being classified as an elite), and specificity (percent likelihood of a novice athlete being classified as a novice; Fig. 2) increase as more PC are retained. Although some tasks level off after retaining 35 PC, some tasks (bird-dog right, drop-jump, hop-down left and right, L-hop left and right, and T-balance left) continue to increase with the more PC retained, meaning that some of the classification rates, sensitivity, and specificity could improve.

Reconstructed motion data (using LDF) allowed visualization of the differences between the elite and novice athletes' movement patterns. For example, during the T-balance right, elite athletes demonstrated greater hip flexion at the beginning of the movement (Fig. 3A), greater forward hip rotation such that their trunk and left leg were more parallel with the ground at the midpoint of the movement (Fig. 3B), and greater hip flexion again at the end of the movement (Fig. 3C) (see Supplemental Digital Content, Figures S8–14, which visually shows and provides detailed descriptions of differences between skill levels for all movements, http://links.lww.com/MSS/B210). Although comparisons rely on visual observation, the differences observed are detected by the data-driven approach. Visualizations provide insight to what the differences are that discriminate between elite and novice athletes. They can also be used to provide feedback to athletes who aim to improve their performance.

The model accurately classified athletes as either elite or novice, so a practical application of the technique was explored. When interpreting the reports, assuming the criterion is to move like an elite athlete, a lower percentage represents poorer movement performance (more novice-like), whereas a higher percentage represents superior movement performance (more elite-like). The two randomly selected athletes were an elite basketball player and a novice golfer. Depending on the task, the elite basketball player's percent likelihood of being an elite athlete ranged from 63.61% (drop-jump) to 99.10% (lunge left) (Fig. 4). For the novice golfer, their percent likelihood of being an elite athlete ranged from 3.42% (drop-jump) to 82.15% (lunge left).

DISCUSSION

The purpose of this study was to assess the ability of a PCA-based pattern recognition technique to differentiate whole-body movement patterns between novice and elite athletes when performing non-sport-specific movement screening movements. The two-staged approach applied PCA to reduce the dimensionality of the complex 3D motion capture data where PC scores were used to develop LDA models for classification. The approach yielded an objective, data-driven model to classify athletes' performance during individual

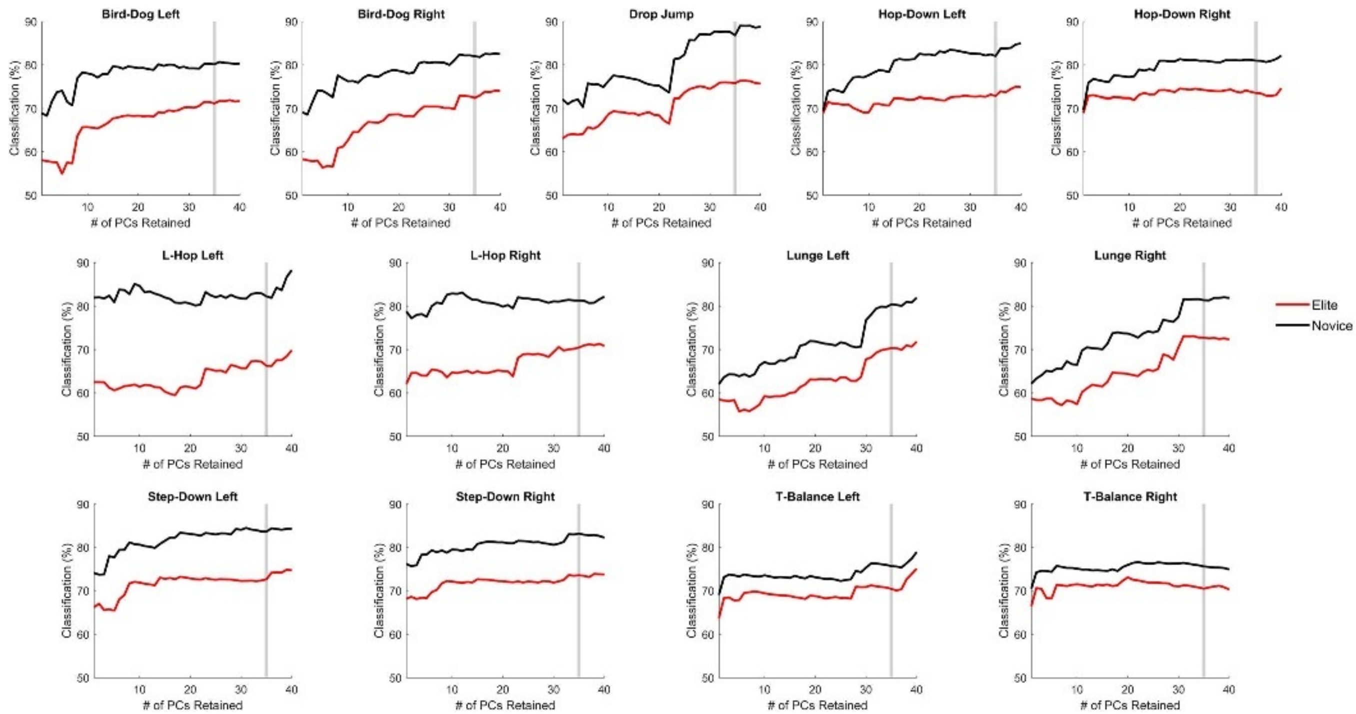

FIGURE 2—The sensitivity (percent likelihood of correctly classifying an elite athlete; *red line*) and the specificity (percent likelihood of correctly classifying a novice athlete; *black line*) for when 1 to 40 PC scores were retained for each movement task. The *vertical gray line* represents the number of PC retained for this study (35 PC).

movement screening movements, where the results supported the hypothesis that movement patterns could be differentiated on the basis of athletes' skill level.

The ability to classify athletes accurately using LDA was movement dependent. The movement dependency of model classification accuracy may be explained by considering the challenge, constraints, and strength needed with each specific movement. On average, the movement tasks that involved jumping (drop-jump, L-hop, and hop-down) had the highest percentage of correctly classified athletes. When looking at the reconstructed data, there are not large differences in distances jumped compared to height. However, there are differences in technique. For the drop-jump (see Supplemental Digital Content, Figure S9, which visually shows differences between skill levels during the drop-jump, http://links.lww.com/MSS/B210), the elite athletes have a greater range of motion of their arm swing, which may result in a greater take-off velocity (32). For the hop-down (see Supplemental Digital Content, Figure S10, which visually shows the difference between skill levels during the hop-down, http://links.lww.com/MSS/B210), elite athletes have greater range of motion of their non-stance leg during the transition from landing to take-off than novice athletes. The nonstance leg is thought to work similarly to the arms during a max vertical jump, where an increase in swing increases upwards momentum. For the L-hop (see Supplemental Digital Content, Figure S11, which visually shows the differences between skill levels during the L-hop, http://links.lww.com/MSS/B210), elite athletes achieve greater jump distance when performing the lateral portion of the jump than the novice athletes. This could be due to the elite athletes achieving a deeper squat when landing from the forward jump, allowing for elite athletes to achieve greater distance during the lateral jump (33). In addition, elite athletes better minimized vertical jump height when jumping for maximal horizontal difference than novice athletes, demonstrating a more efficient jump.

In addition to the jumping tasks, the step-down movements on average had high classification rates. During data collection, athletes often commented on the step-down being the most difficult. It was also the movement that was most often re-collected due to a failure to correctly complete the movement. This suggests that the step-down challenged athletes' mobility and stability more than the other movements. When observing the reconstructed movement patterns,

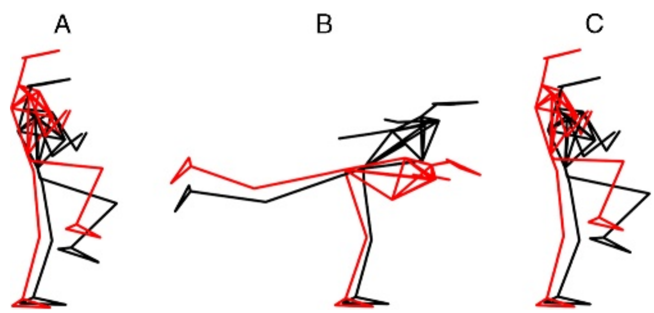

FIGURE 3—Reconstruction of the linear discriminant function differentiating elite and novice athletes during the T-balance right movement at 0%, 50%, and 100% of the movement. Data are reconstructed using the equation: reconstructed data = mean data ± 1 × linear discriminant function. *Red* represents elite athletes, *black* represents novice athletes.

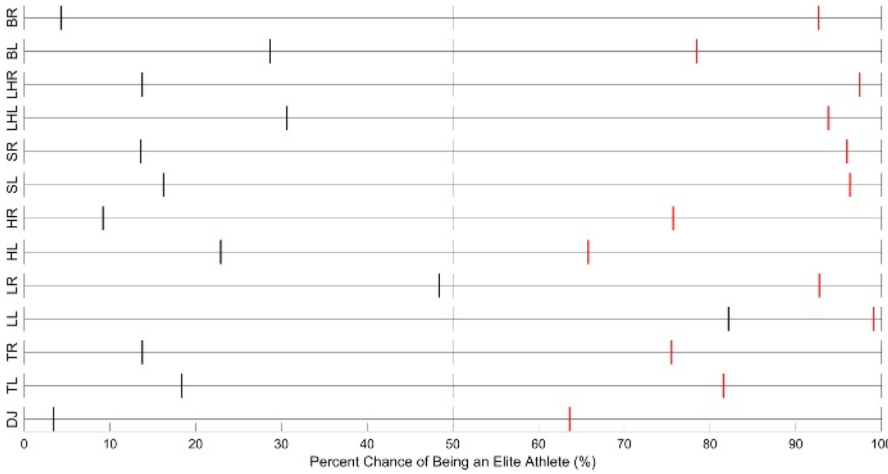

FIGURE 4—An example movement report created for a novice golfer (*black lines*) and a professional basketball player (*red lines*) based on the LDA model and individual PC scores. The scores describe the percent likelihood of the athlete being elite (0%–100%) based on their performance for each movement. BR, bird-dog right; BL, bird-dog left; LHR, L-hop right; LHL, L-hop left; SR, step-down right; SL, step-down left; HR, hop-down right; HL, hop-down left; LR, lunge right; LL, lunge left; TR, T-balance right; TL, T-balance left; DJ, drop-jump.

clear differences between elite and novice athletes can be seen. During the step-down movement, elite athletes used a different movement strategy, moving their center of mass posteriorly to complete the movement.

Because the model accurately classified athletes as either elite or novice, a practical application of the technique was explored. The elite basketball player's movement report is highlighted as the red lines in Figure 4. The elite basketball player had a greater than 50% likelihood of being an elite athlete based on their performance in every movement, however they performed the poorest on the drop-jump and hop-down left. The poor drop-jump and hop-down left performance may be indicative of underlying dysfunction or poor movement, which could prompt the coach or trainer to probe for possible reasons causing the deficiency (e.g., lack of stability, muscle imbalances, poor range of motion). In contrast, the novice golfer generally scored poorly across all movements except for the lunges (Fig. 4), indicative of the golfer's novice status. However, the golfer performed poorest on the drop-jump (3.42% chance of being an elite athlete), which may prompt the coach or trainer to focus on movements related to drop-jump performance. This application of the technique demonstrates how an objective, data-driven method can be used to detect relevant performance differences within a movement screen, in this case using a scoring spectrum related to athlete skill level.

The model developed here improves upon the limitations associated with previous subjective movement screens, such as scores being at the discretion of the test administrator, only observing from one vantage point (13,15), and the test administrator needing to be able to assess multiple scoring criteria at once during quick, dynamic movements (15). The outcome scoring variables proposed in this study are purely objective (although the assessment of differences between the two groups is subjective), scores are not reliant on the discretion of the test administrator and data are collected from multiple cameras at different vantage points allowing for a 360° view of the athlete throughout the movement.

A limitation on the application of this approach for athlete training is the use of movement patterns of elite athletes as the gold standard. Although this is a limitation, because the optimal movement patterns for these movements are unknown, the use of elite athletes as the gold standard is an appropriate option due to their extensive athletic training. To identify optimal movement patterns, future research should focus on using inverse and forward dynamics and optimal-control models to try and identify movement patterns (using the PC scores) that are optimal based on reduced joint loading and minimizing cost functions. Based on results from the models, individuals' movement patterns could be identified on a scale that denotes risk of injury. The identification of optimal movements could lead to better training programs to help decrease injury and improve performance. In addition, because the current methods require an expensive motion capture system, we are currently investigating the use of inexpensive motion capture systems (i.e., inertial movement sensors, inexpensive cameras) to make the use of these methods more accessible to athletes, coaches, and clinicians.

In conclusion, a novel pattern recognition technique using PCA was able to accurately classify athletes based on level of expertise during a movement battery. This technique can potentially be utilized for the training and rehabilitation of athletes and in other fields including ergonomics. Future research should examine other classifiers (i.e., sport played, injury history) and validate the use of inexpensive motion capture systems. In addition, 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 should be explored.

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