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The application of principal component analysis to quantify technique in sports

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Analyzing an athlete's "technique," sport scientists often focus on preselected variables that quantify important aspects of movement. In contrast, coaches and practitioners typically describe movements in terms of basic postures and movement components using subjective and qualitative features. A challenge for sport scientists is finding an appropriate quantitative methodology that incorporates the holistic perspective of human observers. Using alpine ski racing as an example, this study explores principal component analysis (PCA) as a mathematical method to decompose a complex movement pattern into its main movement components. Ski racing movements were recorded by determining the three-dimensional coordinates of 26 points on each skier which were subsequently interpreted as a 78-dimensional posture vector at each time point. PCA was then used to determine the mean posture and principal movements (PM_k) carried out by the athletes. The first four PM_k contained 95.5 ± 0.5% of the variance in the posture vectors which quantified changes in body inclination, vertical or fore-aft movement of the trunk, and distance between skis. In summary, calculating PM_k offered a data-driven, quantitative, and objective method of analyzing human movement that is similar to how human observers such as coaches or ski instructors would describe the movement.

In many sports there is a notable lack of communication between sport scientists (particularly sport biomechanists) and athletes and coaches (Reade et al., 2008a, b). One of the main reasons for this lack of communication might be that scientists and practitioners tend to quantify and analyze athletes' movements in different ways (Loland, 1992). Scientists usually select, record, and interpret specific measurable variables, such as body angles or center of mass (CM) position, to quantify and analyze human movements in sports (Hughes & Bartlett, 2002; Lees, 2002). Practitioners, on the other hand, usually observe the whole-body movement of an athlete, factorize this movement into specific components, and describe the athlete's "technique" as a combination of such multisegment movement components (Knudson & Morrison, 2002; Lees, 2002). For example, in alpine skiing, instructors or technical coaches characterize an athlete's technique by describing specific movements such as "body inclination," "leaning forward/backward," "vertical movement," "upper body rotation," "skidding," and "pole planting" (Österreichischer Skischulverband, 2007; Deutscher Verband für das Skilehrwesen, 2011).

Both the quantitative, analytical approach of scientists and the qualitative, global observations of coaches have certain benefits but also substantial limitations. By singling out specific variables rather than considering the whole movement of an athlete, sport scientists may miss important information and in some cases may not even be able to determine the origin for a change in their observed variables (Lees, 2002). CM movements or changes in the ground reaction force might, for example, be caused by arm or leg movements and can only be interpreted correctly if the movements of all of a body's segments are known and adequately quantified. Focusing on preselected variables therefore often limits the applicability of scientific studies when athletes or coaches want to improve an individual's "technique." In contrast, an experienced instructor or coach can often give very useful practical advice; however, his or her recommendations are typically based on a subjective observation and interpretation of an athlete's movement and may therefore be incorrect or not the best solution for a particular individual.

Two developments of the last two decades make a merger between the scientific and practitioner approaches to human movement assessment possible. First, it has become standard practice in many sport biomechanics laboratories to record the movements of all segments of an athlete in three dimensions using automated three-dimensional (3D) marker tracking technologies. This technology provides large amounts of data that scientists often still handle by determining and analyzing specific variables, for example joint angles or CM movements. However, whole kinematic information is now available to scientists in a way that is similar to a human expert's absorption of whole-body movement characteristics but far beyond a human observer's capabilities in accuracy and speed. Second, pattern recognition methods used to extract features from large data sets or to classify and determine group differences have been applied in sport biomechanics. One such method that can be used for feature extraction is principal component analysis (PCA).

The procedure developed in this study to identify and quantify movement techniques in sports is based on a method first described by Troje (2002) in an analysis of human gait. Troje's main focus was the perception of gait. He has shown that the whole-body movements of gait contain information that allow human observers or computer classification algorithms to distinguish, for example, between males and females (Troje, 2002), young and old, happy or sad, and relaxed or nervous walkers (Sigal et al., 2010). He extracted this information by first separating the whole-body movements into sets of principal movement directions that he called "eigenpostures" and then linearizing the principal movements by approximating them with sinusodial functions. The eigenpostures, as well as parameters needed to define the sinusodial functions (amplitude, frequency and phase), form the feature space that was then used for gait classification (Troje, 2002). Numerous studies have since used this method to further investigate the perception of human movement (Troje & Westhoff, 2006; Provost et al., 2008; Chang & Troje, 2009a,b; Schouten et al., 2010), to develop classification or identification algorithms in gait (Troje et al., 2005; Westhoff & Troje, 2007; Chang & Troje, 2009b), or to develop models for the simulation and animation of human gait (Zhang & Troje, 2007; Chen & Chai, 2010). However, relatively few investigators have applied this or related methods to other forms of human movement or to sports (Donà et al., 2009; Murai et al., 2009; Moore et al., 2011). Donà et al. (2009) applied functional PCA methods to race walking and were able to distinguish knee kinematic and kinetic differences of competitors at differing levels of expertise. Moore et al. (2011) used PCA methods to better understand rider and bicycle motions used for steering and stabilizing a cycle through a range of speeds. Their identification of principal motions of the cycle such as steering, rolling, and yaw were found to be unrelated to principal motions of the upper body. For most of these earlier studies, the "eigenpostures" or principal movement directions were used as the main features for group classification. With the exception of Moore et al. (2011), principal movements have received little attention as individual components that constitute a movement.

We suggest that the principal components of a movement, determined similar to Troje's "eigenpostures" in gait, can be used to quantify the "technique" of individual athletes and might thus provide a methodology to scientifically assess "technique" in sports. This approach might help bridge the communication gap between scientists and practitioners in many sports.

The purpose of the current paper was therefore to illustrate the applicability of PCA for the objective determination of the "principal movements" that comprise technique in a sport. We demonstrate this for the sport of alpine skiing because skiing is a relatively complex movement involving all body segments.

Materials and methods

The primary focus of this paper involves PCA methods, but illustration of these methods as applied to sport requires a relevant data set for the analysis. Therefore, this section will begin with a brief description of the biomechanical methods used to obtain 3D kinematic data in alpine ski racing. Subsequently, PCA methods will be outlined that use this ski data set to demonstrate the potential of PCA as a tool that begins with whole-body observations and objectively extracts the most fundamental motion characteristics captured in the data set.

Collection of ski kinematic data

The data used in the current paper were collected in the framework of a thesis project that is described in detail in Reid et al. (2009) and Reid (2010). In summary, six elite junior ski racers (male, age 17–20, height 1.81 ± 0.02 m, weight 82.7 ± 7.5 kg, International Ski Federation points 22.35 ± 8.21, world rank in their age classes between 1 and 6) were recruited into the study. They gave informed written consent, and the study was registered with the Ombudsman for Privacy in Research, Norwegian Social Science Data Services, AS. The athletes performed three trials under race conditions on a competition-length slalom course where the first portion of the course was set rhythmically with gates 10 m apart and an offset of 2 m. The slope had an average inclination of 19° with hard-pressed and frozen snow conditions typical for race courses in springtime. A volume of $50\,\mathrm{m} \times 10\,\mathrm{m} \times 2\,\mathrm{m}$ containing two full-turn cycles (right and left turns at gates 11 and 12, respectively) was calibrated and equipped with 208 control points that allowed reconstruction of the skiers' motion. Skier movements were captured using four panning and tilting phase alternating line digital video camcorders (50 Hz) that were synchronized postrecording. The fastest trial of each subject was selected for further analysis and manually digitized using a custom-written Matlab program (The Mathworks Inc., Natick, Massachusetts, USA). Object points were reconstructed using the direct linear transformation method (Abdel-Aziz & Karara, 1971). The maximum measurement error of this procedure was calculated to be between 9 and 25 mm; the observed variability of the segment lengths was found between 7 and 14 mm pooled SD (Reid, 2010).

The skiers' movements were quantified by determining 23 points distributed over the skier and the equipment, which indicated the positions of the skier's head, shoulders, elbows, wrists, hands, hip joints, knees, ankles, pole tips, ski tips, and ski tails. These reference points allowed representation of the skier as a stick figure facilitating a qualitative analysis of the skiers' movements (Fig. 1).

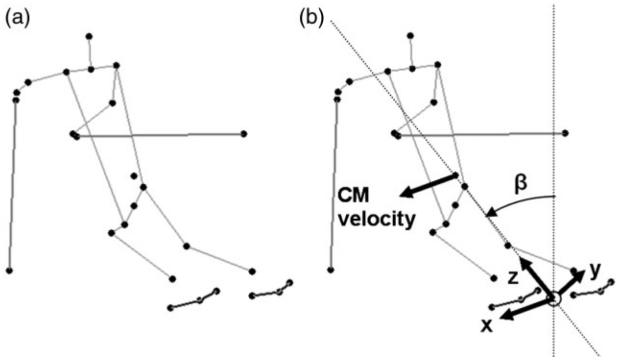

Fig. 1. (a) stick figure representing one subject in a turn to the right. (b) Velocity of the center of mass (CM), body inclination β, and the axes of the reference system for this posture. The x-z-plane represents the sagittal plane; the y-z-plane represents the coronal plane.

In addition to these 23 points on body and equipment, shoulder and hip midpoints were calculated along with the CM position. This was determined for each time frame using Zatsiorsky's (2002) body segment parameters with de Leva's (1996) adjustments, which had been modified to account for the additional masses of the skiing equipment (Reid, 2010). The CM trajectory was filtered with a second-order low-pass Butterworth filter with a 10-Hz cutoff frequency. This was done to avoid noise amplification in the calculation of the CM velocity vector. The other marker coordinates were not filtered.

Reference system

The data set quantifying the movement of the skier in each trial consisted of 137 ± 3 time frames (different number of frames per trial due to different speeds of the skiers) that each contained 78 spatial coordinates (26 3D points on the skier and equipment). In order to analyze the skiing technique, this data set first needed to be transformed from the stationary external coordinate system to an appropriate reference system attached to and moving with the skier. Therefore, a reference system was constructed in which the x-z-plane corresponded to the sagittal and the y-z-plane to the coronal plane of the subject. The midpoint between the two skis was selected as an origin of this reference system. The x-axis pointed in the direction of the CM velocity vector projected onto the plane of the snow surface. The z-axis was determined by calculating the vector from the midpoint of the skis to the skier's CM and by projecting this vector onto a plane perpendicular to the x-axis. The y-axis completed a right-angled, right-handed coordinate system. Hence, this system moved, rotated, and inclined with the skier as he was skiing through the turns.

Data analysis

Similar to Troje's (2002) analysis of gait data, we interpreted the 78 spatial coordinates as a posture vector *P(t)* in a 78-dimensional vector space (posture space). This space was spanned by all 26 reference point coordinates:

$$\overrightarrow{P(t)} = \{m_{1,x}(t), m_{1,y}(t), m_{1,z}(t), m_{2,x}(t) .. m_{26,z}(t)\}$$

where m_i with $i = 1 \ldots 26$ refer to markers 1–26 and t refers to the time index of the selected video frame. At each measurement time point the subject had a specific posture that corresponded to a specific vector in the "posture space." As the subject moved, his posture and thus the vector representing his posture in the 78-dimensional vector space changed. The movements of a subject were therefore represented by the variability of the posture vectors in posture space. The distribution of the posture vectors in posture space was restricted by anatomical limitations and characterized by a high redundancy. A *mean posture* can be calculated for each subject:

$$\overrightarrow{P_{mean}} = mean_{all\ time\ points}\left(\overrightarrow{P(t)}\right)$$

PCA is a mathematical method to determine the direction of the largest variability in high-dimensional data sets (Daffertshofer et al., 2004). The calculation steps for a PCA are (a) removal of the mean; (b) calculation of the covariance matrix of the data; (c) determination of the eigenvalues and eigenvectors of the covariance matrix; and (d) transformation of the original data onto a coordinate system spanned by the eigenvectors of the covariance matrix.

In the application of PCA on the posture vectors as defined here, the removal of the mean represents the subtraction of the mean posture $\overrightarrow{P_{mean}}$. Hence, only changes in posture, or in other words, only relative movements were analyzed. The covariance matrix was 78×78-dimensional. The eigenvector of the covariance matrix with the largest eigenvalue points in the direction of the largest variance of the data set (i.e., it represents the direction of the largest movement of the subject). The second eigenvector represents the direction of the second-largest movement in the subspace perpendicular to the largest movement and so on. The eigenvectors are usually called "principal component vectors" $\left(\overrightarrow{PC_k}\right)$ and ordered according to the amount of variability they represent. The eigenvalues (EV_k) quantify the amount of variability in the direction of the associated eigenvector. They can be represented as absolute values, or they may be normalized by dividing by the trace of the covariance matrix. In the latter case, they represent the relative variability of posture vectors (in %) in the direction of the corresponding eigenvector relative to the variability in the entire data set. The transformation of the original 78-dimensional posture vectors onto a coordinate system spanned by the principal components

$$\overrightarrow{P(t)} = \overrightarrow{P_{mean}} + \sum_{k=1}^{78} c_k(t)\overrightarrow{PC_k}$$

was facilitated by projecting each posture vector onto the principal components yielding the coefficients c_k:

$$c_k(t) = \overrightarrow{P(t)} \cdot \overrightarrow{PC_k}$$

The information in the original data set was highly redundant. Therefore, it was not necessary to consider all 78 principal component vectors. If the eigenvalue EV_k of a principal component PC_k was small, then the movements of the subject in the direction of the associated PC_k were small and hence did not add substantial information about the movements of a subject. Therefore, the data can be represented with a given level of accuracy considering only those PC_k whose EV_k exceed a predefined threshold. For instance, Troje (2002) showed that the first four PC_k together covered 98% of the entire variability of the data set in human gait.

Principal movements

Representing the subject movements as a sum of a mean posture and a set of principal component movements factorized a subject's complex multisegment movements executed during a trial into a set of distinct one-dimensional movements. In order to visually illustrate the principal component movements, we defined "principal movements," PM_k, as

$$\overrightarrow{PM_k(t)} = \overrightarrow{P_{mean}} + c_k(t)\overrightarrow{PC_k}$$

because these principal movements can be transformed back into the original coordinate system consisting of 3D reference points. This allowed the reconstruction and animation of stick figures executing only the principal movements. The individual skiing technique of a subject could then be qualitatively assessed by analyzing the animations of the individual PM_k's. The PM_k were characterized by their eigenvalues EV_k and the magnitude and timing of the coefficients $c_k(t)$. In this paper, the $c_k(t)$ were presented as a function of the inclination angle β because β provided an intuitive characterization of the turn cycles (see Fig. 1). In these graphs, positive values of β indicate a right turn and negative values of β indicate a left turn, which correspond to the first and second turns in the analyzed turn cycle, respectively.

Quantitative comparison of the technique of different athletes

Applying PCA to an individual subject allows a quantification of the subject-specific technique employed in a particular trial. However, different subjects will execute movements differently, leading to a unique set of principal component vectors for each subject, making a direct comparison of different subjects' techniques difficult. Common movement components of different skiers may be compared between subjects if the PCA is conducted on a data set composed of the posture vectors of all subjects (i.e., now one covariance matrix was calculated for all subjects). However, the variance of such a combined data set is caused not only by the movement executed by the subjects but also by the anthropometric differences between the subjects. In this study we were only interested in the variance caused by the movements executed by the skiers. The influence of anthropometric differences was therefore reduced by first calculating and subtracting the mean posture $\overrightarrow{P_{mean}}$ for each individual subject (similar to step 1 as described earlier). Hence, the PCA was then calculated on the data set containing the changes of posture of all six subjects. Differences in the individual skiing technique were then quantified as differences in the mean posture of the subjects and as differences in how the subjects executed the common principal movements.

Results

Individual alpine skiing technique quantified by principal movements

The eigenvalues for the first 10 PM_k are shown in Fig. 2. The first four PM_k together were responsible for 95.5 ± 0.5% of the variance in the posture vectors; the first eight PM_k were responsible for 99.3 ± 0.2% of the variance.

As an example, Fig. 3 shows the first five PM_k of subject A (video 1). The first graph in each row shows the coefficient $c_k(t)$ as a function of the body inclination β. For each PM_k three points (1, 2, 3) of the turn cycle were selected in chronological order where the $c_k(t)$ assumed either a large positive, small, or large negative amplitude. At each point a stick figure gives a visual illustration of the PM_k. In all subjects, the PM_1 represented a change of posture that enabled frontal plane body inclination through outer leg extension and inner leg flexion (Fig. 3,

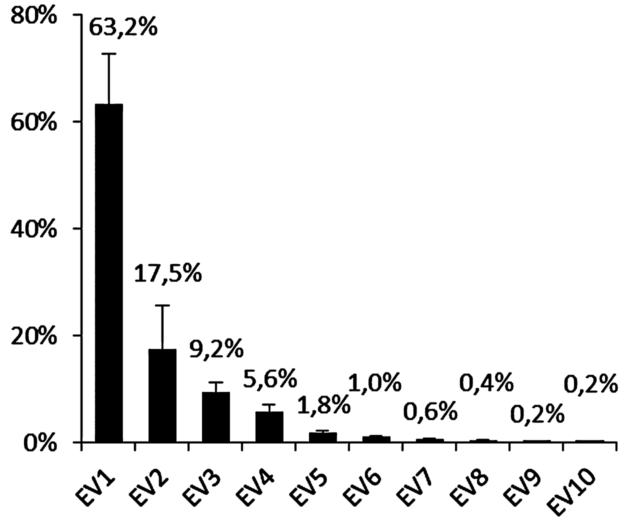

Fig. 2. Mean eigenvalues of the first 10 individual principal component vectors. The bar indicates the mean values over the six subjects; the error bar represents the standard deviation.

first row; video 2). At the same time, the upper body laterally flexed and angled away from the snow surface. Higher-order PM_k were subject specific. In subject A, PM_2 quantified a flexion-extension of the knee and hip joint synchronized with an increase or decrease of the distance between the skis (Fig. 3, second row; video 3). Near the gate, the skier showed an extended posture and a short distance between skis. In between turns, he was in a low body position with a wider distance between the skis. This is a typical technique in a tight slalom course, and all subjects in this study showed it either as PM_2 or as PM_3. PM_3 quantified a rotation of the skis away from the skier's CM velocity (x-axis), which coincided with a rotation of the upper torso (shoulders) around the vertical body axis (Fig. 3, third row; video 4). This rotation of the skis might be related to side skidding and seemed to occur particularly at the end of the second turn (position 3 in Fig. 3, third row). PM_4 quantified a hip-flexion and a crouching of the upper body that coincided with a rotation of the skis about a medio-lateral axis (Fig. 3, fourth row; video 5). At the beginning of the turn (position 1 in Fig. 3, fourth row), the skier was relatively upright. At the end of the first turn (position 2), the skier was in a relatively low position. At the end of the second turn (position 3), the skier was more upright as compared with the first turn, which might have been caused by the side skidding seen in PM_3. PM_5 quantified a rotation of the skis away from the CM velocity in an opposite direction to PM_3 (Fig. 3, fifth row; video 6). Large magnitudes of this movement were found when the skier was maximally inclined (positions 1 and 3). We speculate that this ski rotation might be a mechanism to trigger the upright positioning of the skier's body.

Among the other subjects, most principal movements were similar but often appeared in a different order.

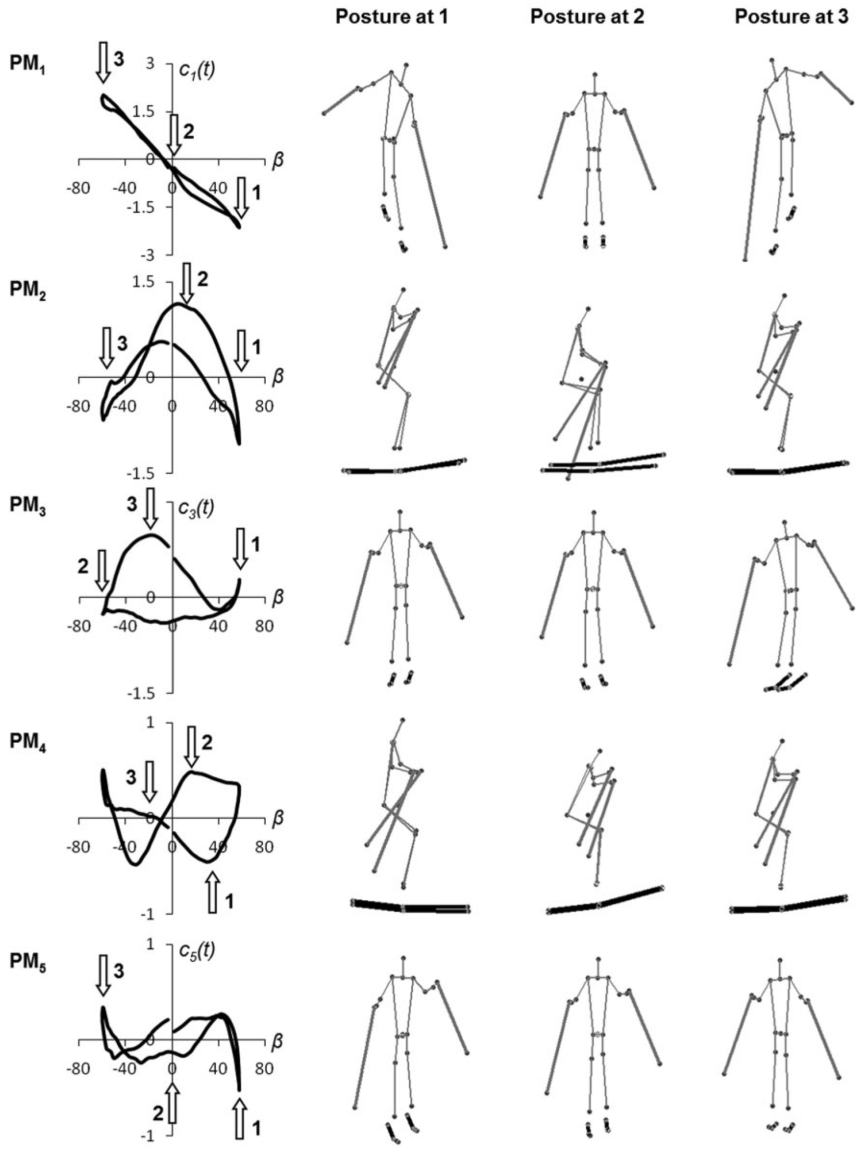

Fig. 3. First five principal movements determined for subject A. The first graph in each row shows the coefficient $c_k(t)$ as a function of the body inclination β. The following graphs represent the principal movement at the time points indicated in the first graph.

Some subjects also showed other combinations of movements; for example, the change of distance between the skis, which was part of PM_2 in subject A (Fig. 3), was sometimes combined with the hip flexion and crouching of the upper body (PM_4 in Fig. 3). Some subjects showed specific movements that did not appear in the other subjects. For example, subject B showed a ski wedge in the initiation of the second turn that appeared in PM_2 (Fig. 4, first row; video 7); subject C showed extensive arm and pole movements, particularly at the end of the second turn, which appeared in PM_2 (Fig. 4, second row; video 8); and unlike the other subjects, subject D used classical pole planting, which caused a stronger rotation of the body visible in PM_3 (Fig. 4, third row; video 9).

Quantitative comparison of the technique of different athletes

Eigenvalues for the first 10 PM_k calculated for the data set containing the change of posture of all subjects are shown in Fig. 5. The accumulated EV_k showed that the largest PMv did not represent the variance in the postures as well as the PM_k calculated for individual subjects. The first four PM_k together were responsible for 88% of the variance in the posture vectors while the first eight PM_k were responsible for 95% of the variance.

The five PM_k with the largest EV_k are represented in Fig. 6. As an example, the techniques of subjects A and C are compared. Subjects A and C reached similar body

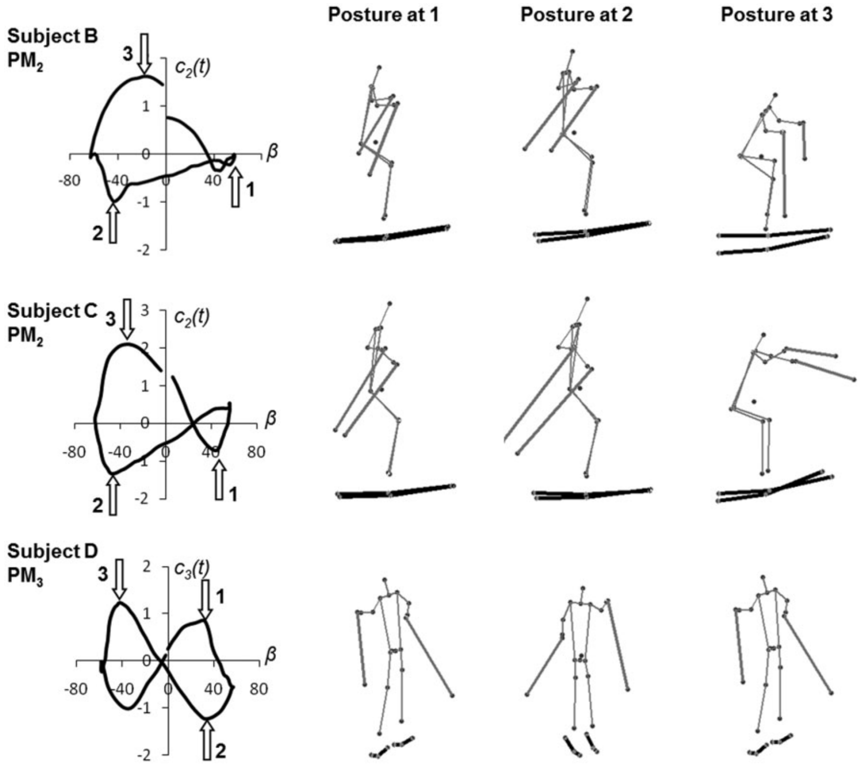

Fig. 4. Subject-specific techniques: ski wedge in the initiation of the second turn (first row, position 3); extensive arm and pole movements (second row, position 3); and rotation of upper body and preparation for classical pole planting (third row).

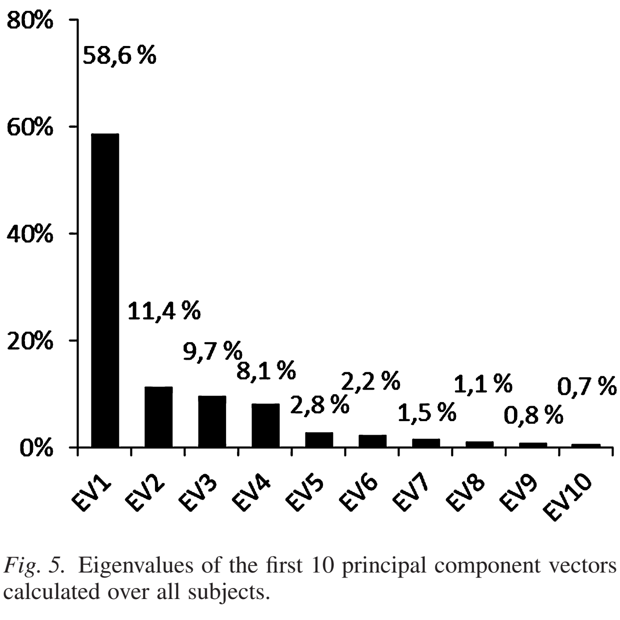

Fig. 5. Eigenvalues of the first 10 principal component vectors calculated over all subjects.

inclinations of 58° and 56° in the right turn and −60° and −62° in the left turn, respectively. PM$_1$ represented a change of posture that enabled the body inclination (Fig. 6, first row; video 10), similar to PM$_1$ calculated for the individual subjects. This movement was similar in subjects A and C. Some of the other subjects showed a hysteresis in PM$_1$, indicating differences in how fast they leaned into the turn as compared with when they returned to the upright posture. PM$_2$ quantified a crouching of the upper body coinciding with a forward movement of the arms and poles (Fig. 6, second row; video 11). The $c_2(t)$-β-graph showed that in this study, the PM$_2$ movement was not carried out to the same extent in the right turn and in the left turn. We speculate that the side inclination of the skiing slope might have caused this asymmetry in how PM$_2$ was carried out. The subjects also showed substantial differences in how they carried out this movement; for example, subject C showed a very extensive PM$_2$ movement in his left turn, which amounted to approximately twice the movement carried out by subject A.

PM$_3$ quantified a vertical motion caused by the flexion of knee and hip joints (Fig. 6, third row; video 12). All subjects tested in this study showed the general inverted U-shape as shown in Fig. 6 for subjects A and C. Small deviations, such as seen in subject C between $\beta = -50°$ and $\beta = -60°$, may indicate, for example, that a subject had to compensate for an unevenness of the ski slope. PM$_4$ quantified a yawing of the skis with respect to the skier's CM velocity (Fig. 6, fourth row; video 13), while the skiers' posture changed similarly to PM$_1$. We speculate that PM$_4$ might be related to side skidding or drifting of the skis. All subjects in this study showed a similar range of the PM$_4$ movement; however, the shape formed in the $c_2(t)$-β-graphs were highly subject specific. PM$_5$

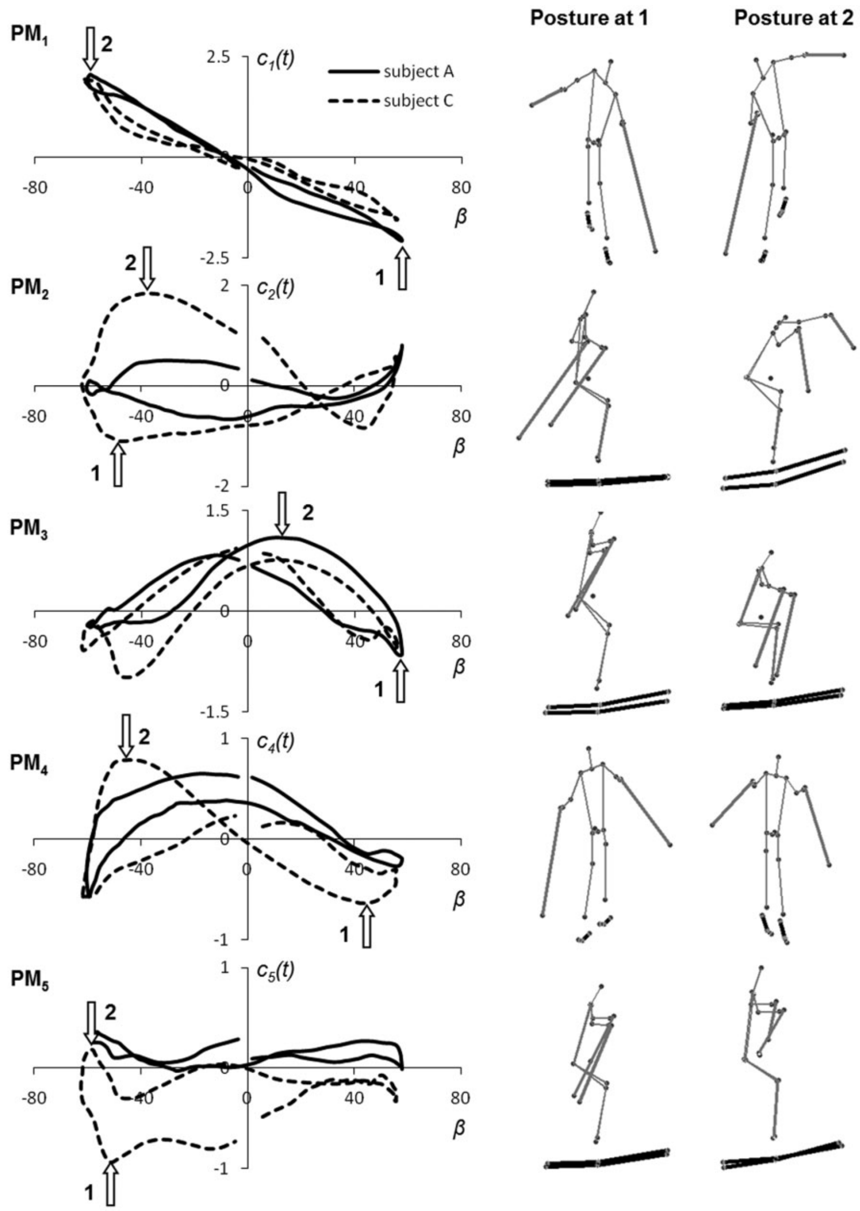

Fig. 6. Common principal movements (PM) calculated for all subjects. Left: a graph comparing the skiing technique of subject A with the technique of subject C for the full-turn cycle. Right: two postures of the subject showing the largest amplitude in this PM displayed for the points specified in the turn cycle.

quantified a backward movement of the upper body coinciding with an outward movement of the poles (Fig. 6, fifth row; video 14). In this study, subject A showed a small range of the PM_5 movement whereas subject C showed this movement extensively.

Discussion

Previous studies analyzing skiing technique measured selected variables that allowed an identification of changes in skiing technique; however, the actual technique of the skiers was described only qualitatively (Müller & Schwameder, 2003; Federolf et al., 2008; Scheiber et al., 2010, 2011). PCA as applied in this study offers a data-driven method to decompose the complex, whole-body movements of a skier into a set of one-dimensional principal movements that can be quantified and analyzed independently. The method of transforming the marker data into a new coordinate system that originates in a mean posture and is spanned by the principal component vectors represents a new perspective of how human movements may be quantified. This new perspective can be considered as similar to the way human observers would characterize and assess movements in sport in that it begins with a whole-body observation. Further, it offers several features that are not available with conventional movement analysis methods. For instance, this approach permits a holistic assessment of the entire movements carried out by an athlete. Moreover, the EV_k quantify the contribution of each PM_k to the entire movement and thus quantify the amount of information that is lost if the analysis is limited to a specific subset of principal movements. The resultant PM_k are purely data driven and therefore are an objective characterization of the observed movement. Different PM_k are uncorrelated but may not necessarily be functionally independent. Further, no variables are preselected for the analysis; hence, no prior knowledge about the movement is necessary. A prerequisite, however, is that sufficient markers were distributed over the subject. The PCA filters out redundant information if more markers than necessary are employed; however, if important information about the movement is not represented in the data, then such information can obviously not influence the result. Finally, the ability to visualize individual PM_k is particularly useful for many practical applications, for example in coaching athletes or in training instructors and coaches.

The accuracy or uncertainty of the principal movements depends on (a) uncertainty of the vector components of the PC_k and (b) on the uncertainty of the $c_k(t)$. The uncertainty of the PC_k vector components depends on the variance in the data set and thus on the variance observed in the marker positions. The method is therefore particularly well suited for highly dynamic movements such as skiing. The $c_k(t)$ are calculated by projecting the posture vectors onto the PC_k vectors which is equivalent to calculating a weighted mean. The accuracy of the $c_k(t)$ can therefore be approximated using the estimates for the uncertainty of weighted mean values.

There are several limitations to the PCA methodology. First, PCA is a linear decomposition method, and it may therefore not remove all redundancy in a data set. A rotation of the subject, for example, will be represented by at least two principal components even though it might be possible to represent it as a one-dimensional movement in appropriate nonlinear coordinates. Second, some PM_k represent a combination of two or more movements that a human observer would consider as independent movements. If, for example, a vertical movement and a rotation of the upper body occur in phase during the movement cycle, then PCA may not be able to separate them. This is particularly critical if large rotations occur in the analyzed movement. In this case, the choice of an appropriate reference system that rotates with the athlete may lead to PM_k that are easier to analyze and interpret. For example, if in this study a reference system would have been chosen that did not rotate and incline with the subject, then more principal movements would have been necessary to represent each subject's skiing technique and the resultant principal movements would have been a combination of rotations and other movements. A further limitation is that while the PM_k quantify the movement as executed by the athlete, the causes for these movements remain unknown. For example, in skiing a movement might be the active actions of the skier or compensatory movements that were necessary due to uneven ground or due to skidding. One solution to this issue would be the analysis of larger data sets containing multiple turn cycles such that individual events would have less influence on the PCA results.

Perspective

This study showed how PCA performed on the coordinates of a full body marker set offers objective and quantitative criteria for an assessment of an athlete's individual technique during complex human actions, such as in alpine skiing. In other sports, similar methods could provide coaches and practitioners new insights into their sport and their athletes' techniques. Particularly the ability to visualize the individual components of a movement will help practitioners to develop a better understanding of how complex movements are executed. When applying the PCA analysis as outlined in this study, it might be useful to consider other normalization procedures, e.g., normalization to unit variance.

This method may find other applications in the near future. One obvious application lies in the biomechanical feedback available for coaches to use when planning the training of athletes, but the method might also support instructors or coaches in developing their skills to assess an athlete's movements. Correlating the principal movements with functional variables such as ground reaction forces or performance variables should also offer a deeper understanding of the functional consequences of an athlete's actions and may therefore help in the improvement of an athlete's technique. Such a functional analysis might also find applications in the development of sports equipment because the movements executed by the athletes define the loading characteristics for the equipment (Federolf et al., 2010). Quantifying the main movement components by principal movements might therefore help to better define appropriate boundary conditions.

Advances in technology will further enhance the proposed method of analyzing technique in sport. Markerless motion tracking is being developed in several laboratories, and accelerometry, inertia, and GPS systems are being combined to quantify human movement over large distances outside the laboratory environment. All of these technologies create a large amount of 3D kinematic data. The PCA methods described in this paper offer a strategy to handle and extract useful information from such data sets in a wide variety of sports.

Key words: human movement analysis, biomechanics, coaching, alpine skiing.

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