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Biomechanical features of gait waveform data associated with knee osteoarthritis
An application of principal component analysis

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Abstract

This study compared the gait of 50 patients with end-stage knee osteoarthritis to a group of 63 age-matched asymptomatic control subjects. The analysis focused on three gait waveform measures that were selected based on previous literature demonstrating their relevance to knee osteoarthritis (OA): the knee flexion angle, flexion moment, and adduction moment. The objective was to determine the biomechanical features of these gait measures related to knee osteoarthritis. Principal component analysis was used as a data reduction tool, as well as a preliminary step for further analysis to determine gait pattern differences between the OA and the control groups. These further analyses included statistical hypothesis testing to detect group differences, and discriminant analysis to quantify overall group separation and to establish a hierarchy of discriminatory ability among the gait waveform features. The two groups were separated with a misclassification rate (estimated by cross-validation) of 8%. The discriminatory features of the gait waveforms were, in order of their discriminatory ability: the amplitude of the flexion moment, the range of motion of the flexion angle, the magnitude of the flexion moment during early stance, and the magnitude of the adduction moment during stance.

Keywords: Gait analysis; Knee osteoarthritis; Principal component analysis; Knee kinematics; Knee kinetics

1. Introduction

Modern gait analysis is a powerful noninvasive tool that offers a unique means of measuring the biomechanical response to diseases of the musculoskeletal system, such as knee osteoarthritis (OA). The large volume of data resulting from gait analysis is highly complex, multidimensional, and correlated. A significant barrier to the clinical use of gait information is the successful reduction and analysis of the data [1].

Most gait data appear as temporal waveforms representing specific joint measures throughout the gait cycle (i.e. knee angles, knee moments). Difficulty arises because the amount of data used to describe even a single waveform is quite large. One of the simplest, most commonly used methods of analyzing gait data is the definition and extraction of parameters (i.e. ranges, peak values) as descriptors of discrete instants or events of the gait pattern [2–4]. Detection of abnormality reduces to finding significant differences between subject group averages of these parameters. Extracting predefined parameters from atypical waveforms is subjective, and parameters neglect the temporal information in gait waveforms.

There has been much work in the area of waveform analysis techniques. These include qualitative comparison and subjective descriptions of the overall shapes of gait waveforms [3,5,6]. Quantitative analysis methods of gait waveform measures include Fourier series, neural network classifiers, and pattern recognition techniques [7–9]. All of these methods consider the entire gait cycle data. In a review of analytical techniques for gait data, Chau [1,10] asserted the usefulness of principal component analysis (PCA) for dimensionality reduction and interpretation. Deluzio et al.

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[11,12] recognized the strong correlations between the time samples of gait waveforms and introduced a novel application of PCA to the analysis of kinematic and kinetic gait waveform measures. The authors were able to quantitatively detect differences in gait waveforms at specific portions of the gait cycle. This work emphasized comparison to a reference or normal gait pattern and detection of pathological deviations from this reference, as well as pre- and post-operative changes.

In the current study, the PCA waveform analysis technique was expanded in a comparison of the gait patterns of two groups of subjects: a group of patients with end-stage knee osteoarthritis and a control group. Principal components were extracted to determine features of variation that could be used to quantify differences in gait patterns between these groups. The objective was to determine the biomechanical features of these gait measures that are related to knee osteoarthritis. Principal component analysis was used as a data reduction tool, as well as a preliminary step for further analysis to determine differences between the OA and the control groups. These further analyses included statistical hypothesis testing to detect group differences, and discriminant analysis to quantify overall group separation and to establish a hierarchy of discrimination ability among the gait waveform features.

2. Methods

The osteoarthritis patient group consisted of 50 elderly patients with severe knee osteoarthritis, who were evaluated prior to total knee replacement surgery. Comorbidity was not assessed, but is probable in people with end-stage osteoarthritis. The control group consisted of 63 elderly asymptomatic volunteers. They were pain-free, without any evidence or history of arthritic disease, or record of surgery to the lower limbs. Subjects signed an informed consent approved by the University Ethics Review Board.

2.1. Gait analysis

The subjects completed five walking trials at a self-selected speed in their regular walking shoes. Three-dimensional gait patterns of subjects were studied with an optoelectronic gait analysis system [13] that incorporated a standardized radiographic technique [14]. Standardized radiographs for all subjects were taken with the knee in a natural standing position, and included an anterio-posterior view of the hip and knee as well as a lateral knee view for the test leg only. X-rays were used to measure static knee alignment, geometry, and muscle moment arms, and to move the positions of the motion tracking system markers to their predetermined bone landmarks. This allowed for accurate transformations from surface marker locations to joint centers. Three-dimensional locations of six infra-red light emitting diodes were measured at 50 Hz. A force plate was synchronized with the global coordinate system of the camera with a motion calibration frame.

An inverse dynamics procedure was used to calculate three-dimensional knee joint angles, moments, and forces with respect to the tibia plateau. The three-dimensional sign convention for the angles, moments, and forces follows an anatomically based coordinate system. The three principal axes at the proximal tibia were termed posterior–anterior (PA), lateral–medial (LM), and distal–proximal (DP). Knee angles were defined according to Grood and Suntay [15] and moments were expressed as net external knee joint moments [13].

Scaled radiographic measurements helped to construct a subject specific knee model used to estimate the forces that generated the joint moments. The knee was modeled as a two-dimensional structure that could be positioned in three-dimensional space [16]. In this model, the sagittal plane moment and the quadriceps' or hamstrings' moment arm were used to estimate the muscle force required to generate the net knee flexion moment. It was assumed that there was no co-contraction of the quadriceps and hamstring muscles and muscle moment arms were considered constant. Segmental inertial properties were estimated using regression equations based on subject specific anthropometrics [17].

The knee flexion angle, adduction moment, and flexion moment were chosen for investigation in this study because their importance to knee osteoarthritis was identified by previous investigators. The dynamic knee adduction moment tends to be higher in patients with knee OA [18,19]. The range of knee flexion in the sagittal plane (knee flexion angle) as well as peak flexion angles [19] is generally lower in patients with knee OA [2–4]. Peak knee flexion moments have also been identified to be lower in knee OA patients [19,20].

2.2. Statistical methods

As a first exploratory step in the analysis of a data matrix with measurements of n subject observations on p variables, principal component analysis is often used due to its potential for data reduction and explanation [21]. The main purpose of PCA is to summarise the most important information in the data. This is accomplished by representing the observations and the variables simultaneously in a limited number of optimal principal components or features. These features are optimal in the sense that they explain a maximal amount of variance in the original variables. Mathematically, PCA consists of an orthogonal transformation that converts the p variables $\boldsymbol{X} = \boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_p$ into p new uncorrelated principal components, $\boldsymbol{Z} = z_1, z_2, \ldots, z_p$. The principal components are mutually uncorrelated in the sample and are arranged in decreasing order of their sample variances. The principal component model is $\boldsymbol{Z} = \boldsymbol{U}^{\mathrm{t}}\boldsymbol{X}$ where the columns of $\boldsymbol{U} = \boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_p$ are called principal component loading vectors, and are the eigenvectors of the covariance matrix of $\boldsymbol{X}$. The eigenvector matrix is orthonormal; therefore, the principal component model can be inverted, $\boldsymbol{X} = \boldsymbol{U}\boldsymbol{Z}$. That is, the original data can be reconstructed from the principal components.

When applied to waveform data, the variables, $\boldsymbol{x}_i$, refer to the individual samples (usually temporal) of the waveform. For example, a time normalized gait waveform sampled at each 1% from 0% to 100% would correspond to an $n \times 101$ data matrix, $\boldsymbol{X}$, where n is the number of subjects. The principal component loading vectors, $\boldsymbol{u}_i$, are an orthogonal basis set for the waveform data. In this way each principal component represents specific features of the waveform data. The principal component score (PC score) vectors, $\boldsymbol{z}_i$, are composed of the coefficients which measure the contribution of the principal components to each individual waveform. In this way, the original waveform data for a particular subject is transformed into a set of PC scores that measure the degree to which the shape of their waveform corresponds to each feature. This transformation is attractive when the features themselves are interpretable. Interpretation of the principal components in this work was accomplished through examining the shape of the loading vector, and the individual gait waveforms that corresponded to high and low PC scores.

2.3. Selection of the number of principal components

A powerful property of principal component analysis is that if the majority of variation is explained by the first few principal components, $\boldsymbol{Z} = z_1, z_2, \ldots, z_k$, where $k < p$, the remaining principal components can be dropped from the model and the reduction in dimension is achieved [22]. The number of principal components, k, needed to build a principal component model which adequately describes a dataset can be found using several criteria that are based on the portion of explained variation. In this analysis, a 90% trace criteria was used to determine the number of principal components to retain in the model [22]. While this could result in discarding some important details, our objective was to explain the majority of variation in the data, and capture the primary modes of variation. Futhermore, the smaller variance PCs can be harder to interpret [12].

2.4. Analysis of group differences in the PC scores

The principal component analysis transforms the gait waveform data to a small set of PC scores for each patient. Therefore, standard statistical techniques can be applied to perform hypothesis tests regarding group differences in the features (PCs) of the waveforms. The principal component scores of the flexion angle, adduction moment, and flexion moment waveforms were analyzed for group differences using Student's t-tests and discriminant analysis.

A stepwise discrimination procedure was used to select the PCs that could separate the two groups. This discrimination procedure indicated which principal components had significant discriminatory power, and should therefore be included in a linear discriminant model to optimally separate the two subject groups. The principal components retained after the stepwise discrimination procedure were included in a linear discriminant function, the optimal boundary of separation of the groups in the multidimensional space [23]. The magnitude of a principal component's coefficient in the linear discriminant function indicated its relative importance in the separation of the groups.

3. Results

Anthropometrics for all subjects are summarized in Table 1. The knee OA patients and the control group of subjects were of similar age, height, weight, and body mass index (BMI). The OA patients walked slower than the age-matched controls.

Principal component models were developed for the flexion angle, adduction moment, and flexion moment waveform gait measures (Table 2). The number of principal components (PCs) in each model was chosen through a 90% trace criterion [22]. The low number of PCs suggested that there was a simple underlying structure to the variability

Table 1
Subject characteristics

Subject group	n	Age (years)	Height (m)	Weight (kg)	Speed† (m/s)	BMI (kg/m^2)
Control group	63	65 (8.5)	1.68 (.09)	80.68 (15.4)	0.95 (0.14)	28.81
Knee OA patients	50	70 (7.8)	1.63 (.09)	86.63 (22.1)	0.76 (0.08)	29.32

The data are presented in the form of mean (S.D.).
† Significant difference ($p < 0.05$).

Table 2
Principal component models

	Knee flexion angle	Knee adduction moment	Knee flexion moment
Variation explained (%)	93.88	91.35	93.63
Number of PCs	3	2	3

Table 3
Group differences in waveform patterns

Gait measure	PC	Feature	Mean (S.D.)		p-Value
			OA	Control	
Flexion angle	PC1	Magnitude of flexion angle throughout gait cycle	−0.47 (1.02)	0.37 (0.82)	0.0013
	PC2	Range of motion	−0.67 (1.02)	0.53 (0.58)	<0.0001
	PC3	Phase shift	0.06 (1.13)	0.05 (0.89)	0.679
Flexion moment	PC1	Magnitude of flexion moment during stance	−0.28 (1.17)	0.22 (0.79)	0.008
	PC2	Amplitude of flexion moment	−0.81 (0.69)	0.64 (0.69)	<0.0001
	PC3	Phase shift	0.04 (0.85)	−0.03 (1.11)	0.717
Adduction moment	PC1	Magnitude of adduction moment during stance	0.63 (1.05)	−0.50 (0.60)	<0.0001
	PC2	Magnitude of adduction moment in first half of stance	0.40 (0.86)	−0.50 (0.95)	<0.0001

The principal components, or features, from each of the gait measures are described. The p-value corresponds to a Student's t-test comparing the PC scores between the normal subjects and the OA patients.

present in the gait waveforms. PC scores were generated for each subject and group differences with respect to these PCs were tested with a Student's t-test. The p-value corresponding to these tests, and the biomechanical interpretation of each PC are provided in Table 3. The waveform data for each gait measure along with the PC loading vectors and waveforms corresponding to high and low PC scores are shown in Figs. 1–3.

The flexion angle revealed differences between the OA patients and the control groups with respect to the first two PCs (Table 3 and Fig. 1). The first PC has all positive values of approximate equal value (Fig. 1B); therefore, it is a measure of the overall magnitude of the flexion angle during the gait cycle. Examination of gait waveforms corresponding to a high and low PC1 score (Fig. 1C) supports this interpretation. The statistical analysis of the PC scores revealed that the OA patients' knees were on average less flexed throughout the gait cycle than the control subjects ($p = 0.0013$). PC2 has large positive values in swing and large negative values during late stance; therefore, it captures the range of motion of knee flexion. Comparison of extreme values of PC2 scores indicates that a high PC2 score corresponded to a large difference between the amount of knee flexion during late stance (30–50% of gait cycle) and midswing (60–80% of gait cycle) (Fig. 1D). The OA subjects had less range of motion during the gait cycle than the control subjects ($p < 0.0001$).

There were group differences in the shape and magnitude of the flexion moment data. The first PC has all positive values of approximate equal value from 15% to 60% of the gait cycle; therefore, it captures the overall magnitude of the flexion moment during stance (Fig. 2B and C). The OA patients had a lower overall magnitude of the flexion moment during stance ($p = 0.008$). The second PC had large positive values in early stance and large negative values during late stance. PC2 was a difference operator that measured the overall amplitude of the flexion moment during the stance phase of gait (Fig. 2B and D). The OA patients were found to have a lower magnitude of positive

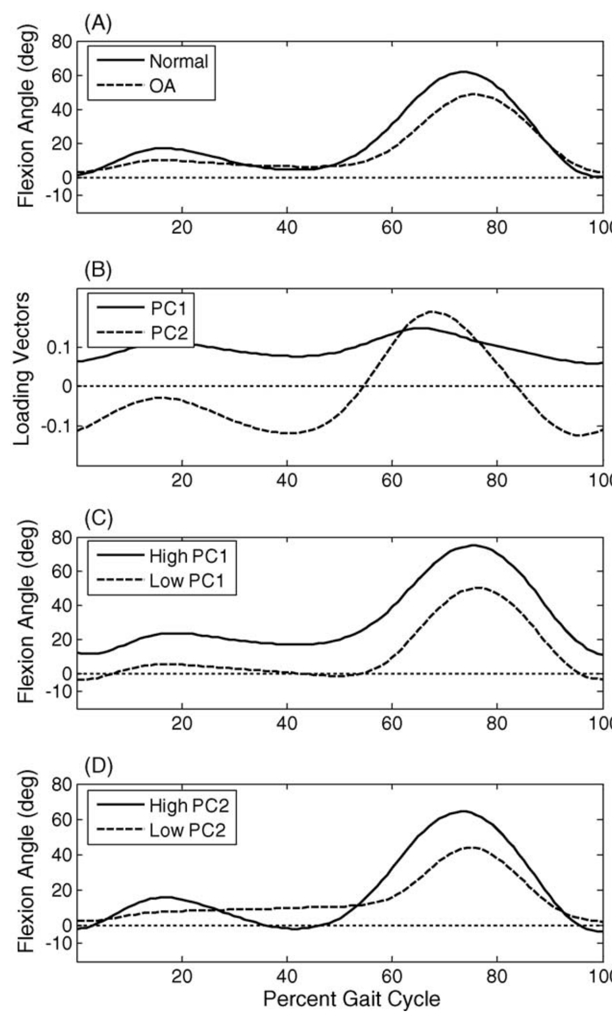

Fig. 1. (A) Mean knee flexion/extension angle waveform data for the OA patients (dashed) and the control group (solid). (B) The loading vectors for the first two principal components, PC1 (solid) and PC2 (dashed). (C) Knee flexion waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC1 scores. (D) Knee flexion waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC2 scores. Comparison of these extremes indicates that PC2 captures the range of motion of the flexion angle.

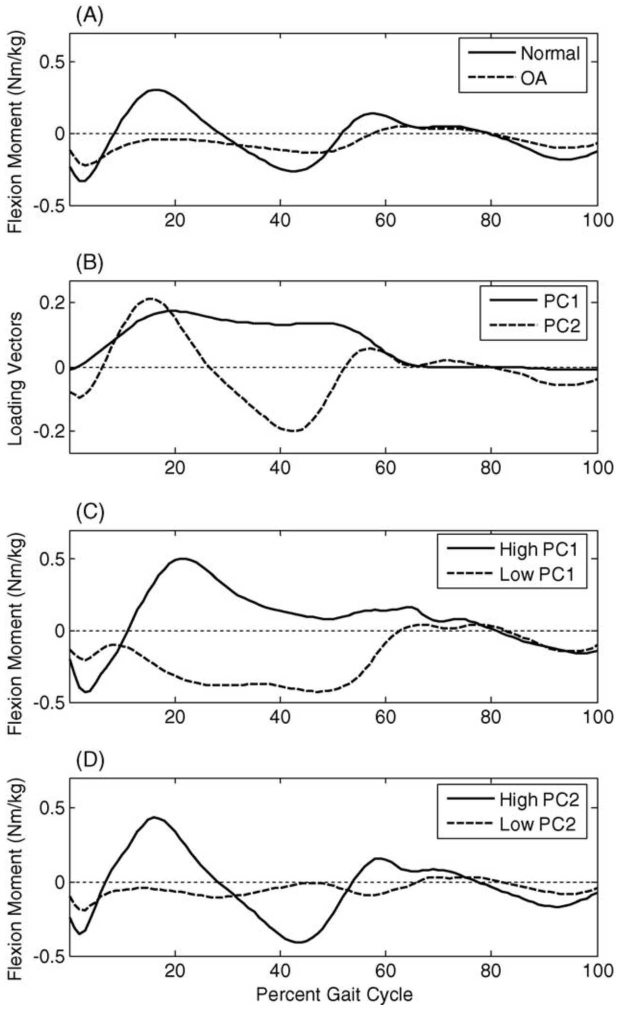

Fig. 2. (A) Mean knee net external flexion/extension moment waveform data for the OA patients (dashed) and the control group (solid). (B) The loading vectors for the first two principal components, PC1 (solid) and PC2 (dashed). (C) Flexion moment waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC1 scores. (D) Flexion moment waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC2 scores.

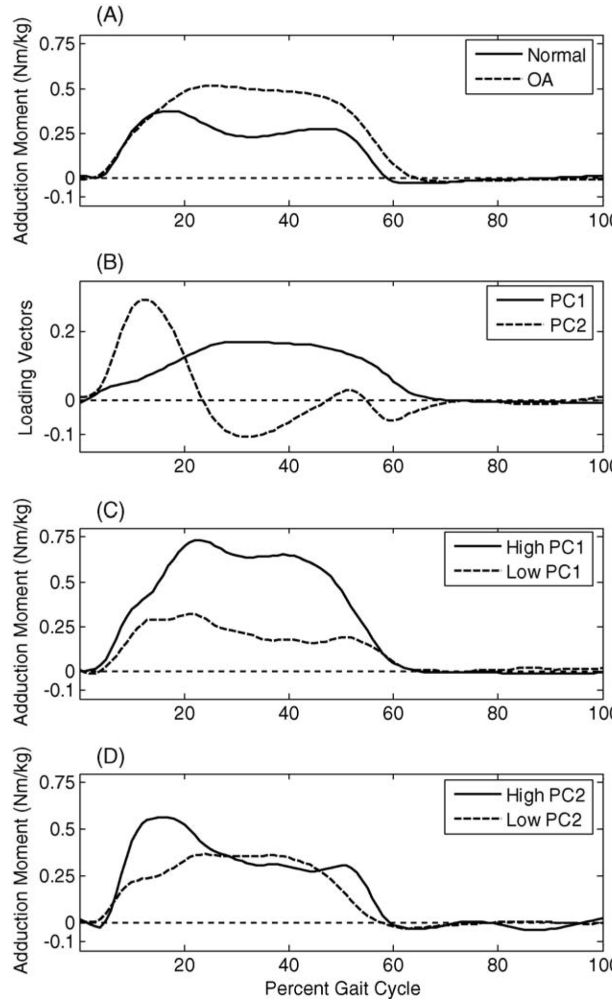

Fig. 3. (A) Mean knee net external adduction moment waveform data for the OA patients (dashed) and the control group (solid). (B) The loading vectors for the first two principal components, PC1 (solid) and PC2 (dashed). (C) Adduction moment waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC1 scores. (D) Adduction moment waveforms corresponding to the 5th (dashed) and 95th (solid) percentiles of PC2 scores.

flexion moment during the first half of stance and a lower absolute magnitude of negative flexion moment (i.e. a smaller extension moment) than the control group ($p < 0.0001$).

The adduction moment was also different between the two groups. The first PC measured the overall magnitude of the adduction moment during stance because it has all positive values of approximate value between 20% and 50% of the gait cycle. It is essentially a weighted average of the adduction moment (Fig. 3B and C). The OA patients had a higher adduction moment than the control group ($p < 0.0001$). The second PC measured the size of the adduction moment during early stance (10–20% gait cycle) relative to midstance (30% gait cycle). The loading vector corresponding to this PC revealed a peak during early stance (Fig. 3B), and the gait waveforms corresponding to high and low PC scores revealed a difference in magnitude during early stance (Fig. 3D). The OA subjects were found to have a lower PC2 score than the control subjects ($p < 0.0001$), corresponding to a lower adduction moment in early stance.

3.1. Discriminant analysis

We were also interested in whether a combination of the principal component scores could be used to discriminate between the two groups. Scatter plots of the PC scores revealed differences in the discrimination ability of each of the PCs. For example, although statistical differences were found with both PC1 and PC2 of the flexion angle, a scatter plot revealed that PC2 (knee flexion range of motion) was more discriminatory (Fig. 4). A stepwise discrimination procedure that included the eight principal components extracted from the flexion angle, adduction moment, and flexion moment waveforms was performed to further

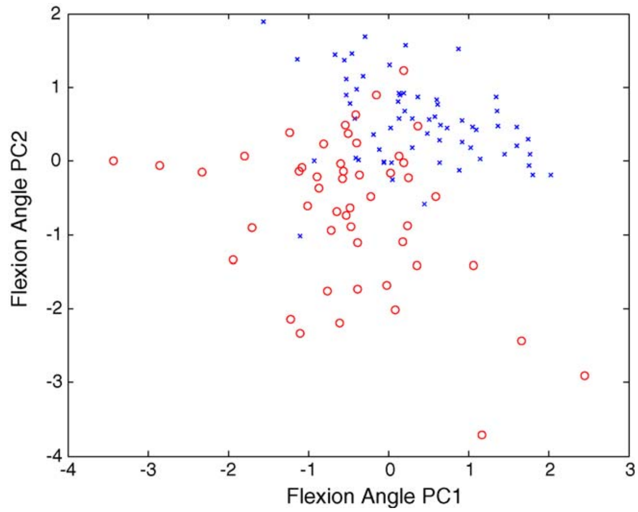

Fig. 4. A scatterplot of the first two principal component scores for the flexion moment waveform data. The OA subjects are coded as "○" and the asymptomatic control subjects are coded as "×". The plot reveals that group separation is primarily in the PC2 direction.

evaluate group separation in terms of the principal component scores. The discriminant analysis was used to quantify overall group separation in terms of the principal components and to establish a hierarchy of discriminatory ability among the principal components.

The discrimination procedure indicated that four of the eight PCs were optimal in defining a discrimination model of the waveform data (Table 4). PCs that explained a large portion of the variability in the waveforms were not necessarily important in group discrimination. For instance, the flexion angle first principal component, although it explained 61.5% of the variation in the flexion angle data, was not included in the discrimination model. The accuracy of the discriminant model was assessed using cross-validation techniques [24]. The misclassification rate was found to be 8%.

A linear discriminant function was defined with the four retained PCs. The discriminant function is the linear combination of the PCs that optimally separates the subject groups. A relative discrimination hierarchy was established by comparing the magnitude of the coefficients of the PCs in the linear discriminant function (Table 4). Sagittal plane measures were the most discriminatory, with the amplitude of the knee flexion moment (flexion moment PC2), and the knee flexion range of motion (flexion angle PC2) being the most discriminatory, and the overall magnitude of the flexion moment and the adduction moment having nearly equal discriminatory power.

Table 4
Discrimination model

PCs retained from stepwise procedure	Linear discriminant function coefficient	Rank of importance in linear group discrimination
Flexion moment PC2	2.22	1
Flexion angle PC2	1.91	2
Flexion moment PC1	1.33	3
Adduction moment PC1	1.32	4

The stepwise discriminant analysis selected the following list of features. The size of the coefficients in the discriminant function indicate the relative importance of each feature to the discriminant function.

4. Discussion

Although hundreds of variables are measured to represent the dynamic gait measure over the gait cycle, the fundamental dimension of gait is much smaller. Principal component modeling of gait waveforms is a promising technique for the successful reduction and analysis of gait waveforms. The methods are more objective and robust than many previously used gait data analysis techniques because: (i) data reduction is based on features that are extracted by the analysis technique, (ii) data from the entire gait cycle data are considered, and (iii) the technique results in a compact set of uncorrelated features that maximally explain the variation in the original data. Other data reduction techniques, such as the subjective selection of parameters from waveforms are popular due to their simplicity. Commonly extracted parameters include peak values, magnitudes at specific gait cycle events, and corresponding time values. Parameter choice, however, is often subjective, and chosen parameters can be highly correlated [25]. It is also often difficult to subjectively choose parameters that can adequately characterize the curves; potentially meaningful parameters can easily be overlooked in subjective parameter extraction.

There is significant variation in the pattern of kinetic knee waveforms between subjects [26], and it can become impossible to define some parameters for all subjects, particularly when dealing with pathological data [27]. For example, in Fig. 1D, while a peak knee flexion angle during stance is easily defined from the control subject's knee flexion angle waveform (solid line), the same parameter is more difficult to define from a flexion angle waveform of a knee osteoarthritis patient (dashed line). Hurwitz et al. [18] encountered a similar problem when trying to extract two peak adduction moments during stance from osteoarthritis adduction moment curves. In the analysis of 13 joint arthroplasty patients, Whittle and Jefferson [5] were unable to identify the peak extension moment in three pathological cases.

The adduction moment PC1 represents a robust measure of the magnitude of the adduction moment during stance, and is a discriminatory PC extracted from the three waveform measures. The adduction moment in the frontal plane is a dynamic alignment measure that has been shown in previous analyses to be higher in patients with knee OA [18,19,28]. Previous analyses have extracted peaks from adduction moment waveforms to compare with Student's t-tests. In some subject waveforms, distinct adduction moment peaks may not exist and adduction moments at particular instants in the gait cycle are chosen to compare. Rather than subjectively selecting which instant during the gait cycle to compare the adduction moments, the adduction moment PC1 represents the overall adduction moment magnitude during the stance phase of the gait cycle.

The proportion of variability described by a principal component does not dictate its ability to discriminate between two groups of observations. A scatter plot of flexion angle PC1 and PC2 scores revealed the level of separation of the normal and OA groups with the first two PCs (Fig. 4). Although the flexion angle PC1 had the greatest pattern of variation among all of the subjects, it is not as discriminatory as PC2, the range of motion principal component. Range of knee flexion motion is therefore a more important parameter to knee osteoarthritis than overall flexion angle magnitude. The importance of the range of knee motion in the sagittal plane to knee osteoarthritis has been identified in previous gait analyses [2–4]). Previous studies have calculated the knee range of motion with parameters extracted subjectively from the waveforms. In this study, principal component analysis utilized the data from the entire gait cycle to quantitatively identify the importance of knee flexion range of motion to knee osteoarthritis. The range of motion principal component represents a robust, quantitatively selected measure for which to compare subjects.

Some gait analysis studies incorporate qualitative, subjective descriptions, and comparisons between the overall patterns of gait waveforms such as joint angles and moments. Separation of subjects into groups is often done on the basis of these patterns. Andriacchi et al. [3] used patterns of the flexion–extension moment curve to classify subjects into groups. The pattern characterised as *normal* was found to occur in 80% of the control subjects. The two abnormal moment patterns tended to maintain an extrinsic moment predominantly tending to either flex the joint (*flexional moment pattern*), or extend the joint (*extensional moment pattern*) throughout the stance phase of the gait cycle. These patterns have been confirmed by others [5,29,30]. Weidenhielm et al. [31] assessed functional outcome by describing the pattern of the stance phase flexion extension curve.

The flexion moment PC2 was the most discriminatory PC extracted from the waveform measures. It represents a shape difference between flexion moment waveforms during stance. As a quantitative measure of curve shape, PCA was used in this study to objectively measure the biphasic pattern, or amplitude, of the flexion moment. PCA removes the need for subjective and qualitative separation of groups based on waveform patterns.

We have presented the details of an important methodology for investigating differences in gait patterns. In this application to knee OA patients, we identified features of gait waveforms that were able to discriminate between knee OA patients and asymptomatic control subjects. Theses features were interpreted in terms of the biomechanical gait measures (i.e. the magnitude of the adduction moment in stance), and they were ranked in their discriminatory power.

It is important to recognize the limitations of this work. This cross-sectional study cannot reveal causative factors of knee OA. It is not possible to determine whether the gait pattern differences are the result, or a contributing factor, of knee OA. There is a need for further work examining differences in gait across the spectrum of disease severity. Longitudinal studies are needed to determine pathomechanical factors of knee OA. Furthermore, the gait differences observed in this study may have been affected by differences in walking velocity. Some of the differences we observed, like the flexion angle component could be due to the walking speed alone, but others such as the increase in the adduction moment are more likely due to the OA. At issue is the fact that the effect of speed on gait mechanics is not fully understood.

5. Conclusion

In the discrimination of subject groups of gait waveform measures, these results confirmed the utility and benefit of using the combination of two multivariate statistical techniques, principal component analysis and discriminant analysis. Principal component analysis fulfills two objectives of gait analysis. It objectively reduces the large quantity of data that is used to describe gait waveform measures, and extracts discriminatory principal components that describe important differences between normal gait patterns and those of patients with knee osteoarthritis. The discriminant analysis was able to rank these features from the gait measures in terms of their power to separate normal and OA gait patterns.

The PCA waveform analysis technique used in this study identified gait pattern differences in the knee flexion angle, the knee adduction moment, and the knee flexion moment. Important differences with knee osteoarthritis included smaller knee flexion moments during stance, larger knee adduction moments during the stance phase of the gait cycle, and smaller knee flexion angle ranges of motion throughout the gait cycle.

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