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The Classification of Anatomic- and Symptom-based Low Back Disorders Using Motion Measure Models

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Study Design. This study observed the trunk angular motion features of healthy subjects and those experiencing chronic low back disorders as they flexed and extended their trunks in five symmetric and asymmetric planes of motion. Trunk angular position, velocity, and acceleration were evaluated during several cycles of motion.

Objective. The trunk angular motion features of the low back disorder group were normalized relative to the healthy subjects and used to 1) evaluate the repeatability and reliability of trunk motion as a measure of trunk musculoskeletal status, 2) quantify the extent of the disorder, 3) determine the extent to which trunk motion measures might be used as quantifiable means to help classify low back disorders.

Summary of Background Data. Given the magnitude of the low back disorder problem, it is problematic that there are few quantitative methods for objectively documenting the extent of a disorder. Impairment ratings of low back disorders can vary by as much as 70% using current systems. Diagnoses and classification schemes are rarely based upon quantitative indicators and we are unable to easily assess and diagnose low back disorders. It is important to quantitatively evaluate low back disorders so that proper treatment can be administered and the risk of exacerbating the problem can be minimized.

Methods. Three-hundred-thirty-nine men and women between 20 and 70 years old who had not experienced significant back pain were recruited as the healthy subjects in this study. One hundred-seventy-one patients with various chronic low back disorders also were recruited and compared with the healthy group of subjects. All subjects wore a triaxial goniometer on their trunks that documented the angular position, velocity, and acceleration of the trunk as the subjects flexed and extended their trunks in each of five planes of motion. Trunk motion features first were normalized for subject gender and age. Several two-stage eight-variable models that account for trunk motion interactions were developed to classify the 510 healthy and low back-injured subjects into one of 10 anatomic- and symptom-based low back disorder classification categories.

Results. Using conservative cross-validation measures, it was found that the stage one eight-variable model could correctly classify more than 94% of the subjects as either healthy or having a low back disorder. One of the stage two eight-variable models was able to reasonably classify the patients with low back disorders into one of 10 low back disorder classification groups.

Conclusion. The motion-related parameters may relate to biomechanical or learned sensitivities to spinal loading. This study suggests that higher-order trunk motion characteristics hold great promise as a quantitative indicator of the trunk's musculoskeletal status and may be used as a measure of the extent of a disorder and as a measure of rehabilitative progress. Furthermore, once the interactive nature of these trunk motion characteristics is considered, the model could help diagnose low back disorders. However, independent data sets are needed to validate these findings. [Key words: diagnoses, dynamic trunk performance, impairment evaluation, low back disorders, patient classification, rehabilitation] **Spine 1995;20:2531–2546**

Low back disorders (LBDs) are one of the most frequently reported musculoskeletal problems, the second most common reason care is sought from a physician, and the second leading cause of absenteeism from work in the United States.[37] Given the prevalence of LBDs, it is problematic that there are few quantitative means to objectively document the extent of a disorder. Impairment ratings of LBD can vary by as much as 70% using current systems.[15] Low back disorder diagnoses and classification schemes rarely are based on quantitative indicators and we are unable to easily assess and diagnose LBDs. Spratt et al[39] emphasized this point via an estimate that a precise diagnosis is unknown in 80% to 90% of disabling low back disorders.

An accurate measure and diagnosis of LBD is desirable for several reasons. First, an accurate measure of LBD status provides a measure by which the extent of the disorder can be judged and by which the degree of progress can be measured. Second, an accurate diagnosis is needed for prescribing appropriate treatment. Mis-

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interpreting the source of LBD can result in treatments that may exacerbate and prolong the LBD event. Third, an accurate diagnosis facilitates the avoidance of situations that may lead to further injury, compounding the disorder. When a quantitative description of the patient's abilities is compared with a quantitative description of job demands, an objective means of determining whether the patient can successfully perform the work is available. Finally, accurate diagnoses minimize the risk that the patient will be exposed to unnecessary diagnostic tests and unnecessary surgery.

Low back disorders are assessed and classified in several ways. Traditionally, physicians have attempted to identify a pathoanatomic source of the LBD. In this approach, patients are classified according to the presumed structure that is injured or painful. Imaging techniques such as computed tomography, magnetic resonance imaging, and myelography are used to help identify the structure that has been compromised. However, a pathoanatomic diagnosis has been found in fewer than 15% of patients with LBD.[27] In addition, it has been estimated that more than 25% of healthy asymptomatic individuals may have imaging-based evidence of a disc herniation. Thus, anatomically based diagnoses are difficult to quantify, difficult to identify, and may incorrectly identify the source of the structural problem.

To overcome these limitations in anatomically based diagnoses, the Quebec study classification system has been developed.[38] This classification accounts for the fact that structural abnormalities are not always identifiable in LBD and recognizes that LBDs are time dependent. This classification scheme is based upon patient symptom reports and can take patient history into account. However, common symptoms can arise from different structural problems, thus confounding the diagnosis. Symptoms cannot be well quantified and can be only a gross measure of the extent of the disorder. In addition, the system may limit the prescription of optimal treatment modalities and may not trigger the use of precautionary measures to avoid re-injury.

The final LBD evaluation system consists of functional assessments. Functional assessments attempt to measure the functional capacity of the trunk's musculoskeletal system.[4,17,34,35] Traditionally, these systems have attempted to measure the amount of force or strength the patient is willing to generate under isometric, isokinetic, or isodynamic conditions. These systems do provide a quantifiable measure of force that can be compared with a normative group. However, these strength measures usually require maximal voluntary force to be exerted against a set resistance. Therefore, strength may be limited by pain tolerance, which is known to vary widely between people. There also is a low correlation between strength measures using different measurement technologies.[34] In addition, these tests may be associated with a risk of injury.[3]

The notion that functional assessment can reveal the status of the trunk's musculoskeletal system is appealing because it lends itself to a set of quantifiable measures that can take into account the co-activation of many of the force generating structures in the trunk, and may provide a summary of the trunk's neuromuscular status. However, many of these traditional measures of function may not be able to measure the "natural" status of the trunk. The strength testing dynamometers externally load the trunk to the point where trunk performance no longer reflects the learned or pattern of coordinated effort of the trunk's neuromuscular control system. As an alternative, Marras and Wongsam[24] used trunk motion characteristics to quantify the trunk's unloaded free-dynamic activity in patients with LBD and healthy subjects. They found that trunk angular velocity distinguished well between the two groups and concluded that the measure held great promise for quantifying the extent of an LBD. The present study will extend this concept to include more comprehensive three-dimensional measures of motion and will investigate the ability of such measurement sets to quantify and classify LBDs.

This research had several goals. The first was to evaluate the repeatability and reliability of free-dynamic three-dimensional trunk motion as a measure of the trunk's musculoskeletal status. The second was to determine whether a method could be established for quantifying the extent of a disorder based on trunk motions. The final goal of the research was to determine the extent to which trunk motion measures might be used as a quantifiable means of classifying LBDs.

■ Methods

The experimental design used in this study assumed that by observing motion characteristics as a function of various asymmetric bends of the trunk, a composite measure of the trunk musculoskeletal control system could be established. During symmetric lifting motions, dynamic motion characteristics are controlled primarily with the large, well-developed muscles such as the erector spinae.[32] However, during asymmetric exertions, motor control becomes more complex and a combination of the smaller less developed muscles (such as the internal and external oblique groups) would be expected to synchronously control a precision bending motion of the trunk.[23] We believed that this change in the primary control muscles would result in a reduced range of motion and in a reduction of the dynamic motion characteristics when a precision bending task became more asymmetric. This change would be detectable and quantifiable by monitoring three-dimensional trunk motion characteristics. Previous studies[21] have shown that this is indeed the case for healthy subjects. The current study will extend this concept to those suffering from various categories of LBD to determine whether the presence of various pathoanatomic conditions and symptoms could be quantitatively identified via the motion characteristics or "motion signature," compared with healthy uninjured subjects.

To achieve this goal, the role of factors other than LBD that may affect trunk motion also must be considered. These factors would be expected to include age and gender. Hence, the effect of these factors on trunk motion also must be evaluated independently from the effects of LBD status.

Experimental Protocol. An experiment was developed to solicit the trunk motion characteristics or motion signature response to flexion and extension trunk bending motions. In a repeatability study, 20 healthy subjects were tested once a week for 5 consecutive weeks. In the main study, a group of healthy subjects and a group of subjects with various LBDs were tested. In both studies, subjects were asked to flex and extend their trunks repeatedly in various symmetric and asymmetric planes of movement while the three-dimensional motion characteristics of the trunk were monitored. No external resistance or load was applied to the trunk during these tests. During the testing session, the subjects viewed a display screen that indicated the instantaneous twisting (asymmetric) position of the trunk. A twisting position target (±2°) also was identified on the screen. The subjects were asked to repeatedly flex and extend their trunk at their preferred speed while maintaining their twisting position within the target. If the twisting position fell outside the target during the trial, a tone was automatically sounded and the trial was repeated. Thus, it was possible to monitor the free dynamic natural motion characteristics of the trunk without physically restricting or interfering with the trunk motion.

Subjects. Ten males and ten females who had never experienced a LBD were recruited to be subjects in the repeatability study. The age of this group was 27 ± 4.8 years (mean ± standard deviation), the height was 171 ± 7.7 cm, and weight was 66.5 ± 8.1 kg.

In the main study, the normal subject population consisted of 339 men and women 20–70 years old who claimed to have never experienced significant back pain. The number of subjects of each gender and the number of subjects within each decade of age are shown in Table 1. One-hundred-seventy-one patients with various LBDs were recruited from the practices of two of the authors (RRC and SRS), which are secondary and tertiary referral practices for LBDs. Consequently, symptoms generally had been present for more than 7 weeks at the time of evaluation. Thus, the patients were considered to have a chronic LBD. Of these subjects, 96 were men and 75 were women. Only patients with a well-diagnosed LBD were included in this study to avoid confounding. Anthropometric characteristics of the healthy and LBD groups also were considered. Of the anthropometric characteristics, only standing height was similar between the two groups. Trunk breadth and depth dimensions generally were 2 cm larger for the LBD group, while spine length and leg length generally were 1–3 cm shorter for the LBD group.

Table 1. The Number of Healthy Subjects Tested Shown as a Function of Age and Gender

	Normal Subjects					
Sex	All Age Groups	20s	30s	40s	50s	60s
Male	193	67	38	38	25	25
Female	146	45	25	26	24	26
Total	339	112	63	64	49	51

Table 2. LBD Classification Showing the Number of Patients and Percentage of Total Patients With LBD in Each Category

Category	Number of Patients	Percentage of Total
Quebec 1	16	9.4
Quebec 2	17	10
Quebec 3	17	10
Spondylolisthesis	16	9.4
Herniated disc pain >3	30	18
Herniated disc pain ≤3	12	7
Stenosis	26	15
Quebec 9.2	11	6
Nonorganic	17	10
Quebec 11	9	5.2
Total	171	100

LBD Classification. In this study, we analyzed trunk motion differences among 10 patient categories that included anatomic classifications as well as pain location categories generally corresponding to those of the Quebec Task Force. The following 10 categories were evaluated.

1. Low back pain with proximal radiation (Quebec Class 2).
2. Low back pain with distal radiation (Quebec Class 3).
3. Localized low back pain (Quebec Class 1)
4. Isthmic spondylolisthesis.
5. Lumbar disc with herniated nucleus pulposus (HNP) with minimal or no pain—3 or less on a 10-point analog visual scale (HBP < 3).
6. Lumbar disc with HNP with moderate or worse pain—greater than 3 on a 10-point analog visual scale (HNP > 3).
7. Spinal stenosis
8. Postoperative patients with pain (Quebec Class 9.2)
9. Patients with evidence of significant nonorganic pain components.
10. Other diagnoses, predominately idiopathic scoliosis (Quebec Class 11).

The number of subjects associated with each LBD classification group is shown in Table 2. The list of categories was finalized after considerable analysis of the clinical and practical issues.

This set of categories discriminates between those herniated disc patients who have minimal or no pain and those who have more severe pain. Patients had varying degrees of relief after nonsurgical management of lumbar disc herniation, and we speculated that the lumbar motion may vary greatly with pain severity. Patients with isthmic spondylolisthesis were evaluated as a distinct category. Although no specific category exists for this diagnosis within the scheme of the Quebec Task Force, we believe that isthmic spondylolisthesis is a sufficiently distinct structural anomaly to warrant evaluation for specific motion characteristics. There were too few patients with degenerative spondylolisthesis to permit their inclusion in this study.

The patients with low back pain, with and without varying radiating pain (Quebec 1, 2, and 3), included patients who (at various points through their treatments) underwent specific

imaging tests that were negative for any significant neural compression, and patients who had never been subjected to such imaging. Because those with distal radicular pain without prior imaging may represent patients with lumbar disc herniation, they were excluded from this analysis. In addition, patients who could not be classified because of insufficient clinical information were excluded, as were those with overlapping diagnoses, such as spondylolisthesis and disc herniation.

The presence of potential nonorganic components of individual patients' pain syndromes, which could affect volitional movement, was recognized. For most patients, signs of nonorganicity were recorded in five categories: 1) superficial tenderness, 2) overreaction, 3) regionalization of symptoms, 4) variation of exam with distraction, and 5) simulation maneuvers.[43] Patients were considered to have a significant nonorganic pain component if signs in more than three categories were present or if elevation of the Hs or Hy scale was seen on Minnesota Multiphasic Personality Inventory testing.

Experimental Design. Five asymmetric positions of the trunk were tested in this study. Asymmetry was defined as the amount of trunk twist in the transverse plane of the body. Asymmetry was set at five levels: 1) a sagittally symmetric position (0), 2) 15° of twist to the right (15 right), 3) 15° of twist to the left (15 left), 4) 30° of twist to the right (30 right), and 5) 30° of twist to the left (30 left). These asymmetric lines of action are illustrated in Figure 1. The initial testing position for each subject consisted of the 0 condition followed by the two 15° conditions, followed by the two 30° conditions. The order of the right and left conditions were counterbalanced in the experimental design. Subjects were not always able to perform all conditions.

Twenty-six dependent variables were observed in this experiment as a function of each asymmetric condition. The ability variable simply described the capability of the subject to complete the various experimental conditions. The second variable consisted of twisting range of motion (ROM) capability (not part of experimental conditions). Fourteen trunk motion characteristics or features were observed as a function of the experimental conditions. These characteristics consisted of the following.

1. The ROM (difference between maximum and minimum position) in the sagittal plane.
2. Range of motion in the frontal plane.
3. Range of motion in the transverse plane.*
4. Peak flexion velocity in the sagittal plane.
5. Peak extension velocity in the sagittal plane.
6. Peak flexion acceleration in the sagittal plane.
7. Peak extension acceleration in the sagittal plane.
8. Peak right lateral (frontal) bending velocity.
9. Peak left lateral bending velocity.
10. Peak right lateral bending acceleration.
11. Peak left lateral acceleration
12. Peak right axial velocities in the transverse plane.*
13. Peak left axial velocity in the transverse plane.*
14. Peak right axial acceleration in the transverse plane.*
15. Peak left axial acceleration in the transverse plane.*

* These motion characteristics were limited by the experimental conditions.

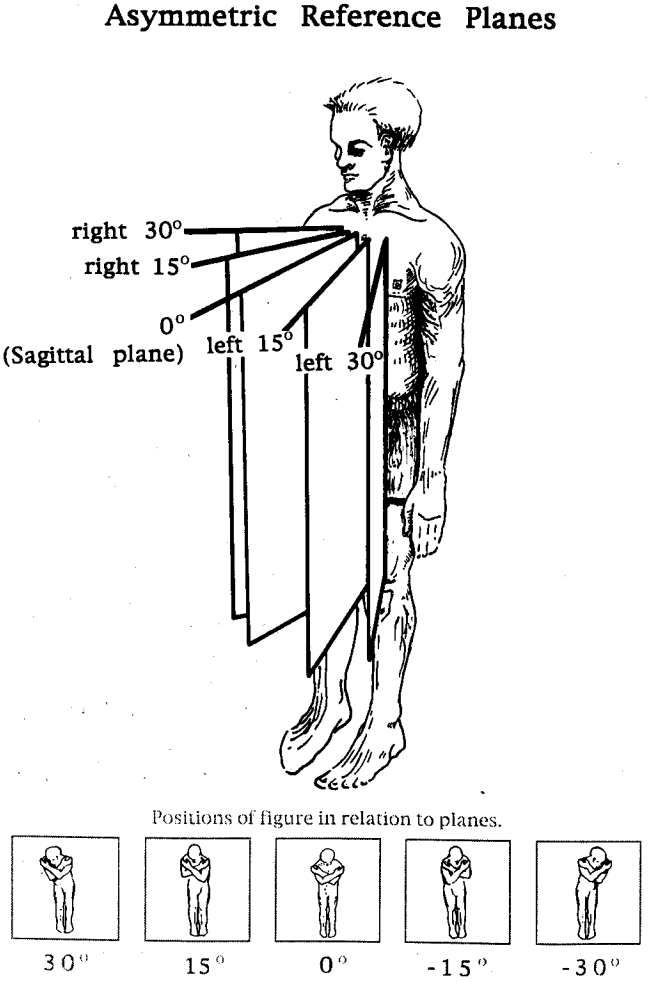

Figure 1. Asymmetric planes defining the testing conditions.

Finally, 10 weighting coefficients were used to characterize the continuous nature of each of the angular position, velocity, and acceleration profiles in the sagittal plane. These coefficients were computed based on the optimal feature extraction procedure that enabled us to accurately reconstruct the continuous profiles while reducing the dimensions of the original data.[33]

Apparatus. The trunk's three-dimensional dynamic trunk motion characteristics were monitored in this study with a triaxial electrogoniometer. This device was developed in our laboratory and is referred to as the lumbar motion monitor (LMM). This device has been used previously to document trunk motions used by workers in industry.[22] The LMM is an instrumented exoskeleton attached to the shoulders and pelvis. It measures the difference in trunk position of primarily the lumbar spine (as a unit) relative to the pelvis. The LMM signals were sampled at 60 Hz via an analog-to-digital converter and a portable 386-based microcomputer. After the data were collected, the signals were processed in the laboratory to determine position, velocity, and acceleration of the trunk as a function of time in the sagittal, frontal (lateral), and transverse (axial twisting) planes of the body. Voltage readings from the potentiometers were converted into angular position in the cardinal planes using a regression (calibration) model

(R^2 = 0.978 sagittal, 0.976 lateral, 0.983 twisting). The angular velocity and acceleration were obtained through numerical differentiation. Filtering (to eliminate noise) also was performed before differentiation of the signal.[36] Validation studies[20] indicated that the LMM's measurement of trunk angular position, velocity, and acceleration in three-dimensional space was similar in accuracy to that of video-based motion assessment systems. Note that LMM-generated acceleration estimates were not directly compared with accelerometer readings. However, others using this differentiation technique have found that it relates well to measured acceleration.[36] The transverse plane position signal from the LMM was wired to a comparator circuit that provided feedback to the subject so transverse plane motion, and thus the asymmetric experimental conditions, could be controlled.

Measurement Repeatability. To assess the repeatability and reliability of the LMM testing protocol, an initial study was performed. Twenty normal subjects performed the experimental protocol on five separate testing occasions, with a 1-week period separating each testing session. The trunk motion characteristics in the sagittal and frontal planes were compared over the five testing periods. There were no statistically significant differences among the trunk motion characteristics between the five testing sessions (multivariate analysis of variance, $P > 0.05$). Cronbach's alpha correlation coefficients (reliability measure) were computed for the trunk motion variables considered in this study. These correlations are shown in Table 3 as a function of the various trunk motion measures. These correlations varied as a function of the experimental conditions with the 0 conditions yielding the best correlation coefficients. Correlations in the other conditions and those associated with the continuous variables varied greatly. Table 3 served as a rationale for selecting motion variables that would be acceptable for the LBD quantification and classification. Only variables with Cronbach's correlation coefficients above 0.8 were considered for model classification purposes. This practice conformed to previous guidelines.[29,44]

Table 3. Cronbach's Alpha Correlation Coefficients for 20 Subjects

	Task Asymmetries				
Motion Features	Zero	15° Right	15° Left	30° Right	30° Left
Sagittal range of motion	.96	.91	.90	.94	.95
Sagittal flexion velocity	.96	.94	.93	.95	.95
Sagittal extension velocity	.95	.94	.93	.95	.95
Sagittal flexion acceleration	.95	.95	.94	.94	.95
Sagittal extension acceleration	.95	.96	.95	.93	.95
Lateral range of motion	.88	.72	.89	.47	.89
Lateral right velocity	.92	.62	.87	.57	.89
Lateral left velocity	.91	.65	.84	.73	.93
Lateral right acceleration	.92	.65	.86	.72	.83
Lateral left acceleration	.91	.61	.88	.78	.87

	Continuous Motion Characteristics		
Continuous Coefficients	Position	Velocity	Acceleration
1	.94	.95	.95
2	.77	.80	.85
3	.78	.84	.88
4	.87	.86	.93
5	.76	.72	.77
6	.73	.13	.91
7	.82	.78	.89
8	.72	.29	.87
9	.82	.33	.89
10	.69	.57	.79

Additional Motion Features	
Twist position right	1.00
Twist position left	1.00
Twisting range of motion	1.00
Ability	1.00
Number of peak accelerations during flexion at task asymmetry zero	0.74
Number of peak accelerations during extension at task asymmetry zero	0.87

Coefficients describe repeatability of motion features at all five task asymmetries, continuous characteristics at task asymmetry zero, and additional motion characteristics.

Procedure. Subjects were asked to observe a visual display representing the transverse plane trunk position. This display tracked the subjects' twisting position by representing the transverse angle as a dot on a screen display. The subject was instructed to twist so their transverse plane position dot moved within the target zones representing the desired asymmetric condition. Subjects were given six instructions. These were: 1) cross arms in front of chest, 2) stand with feet shoulder width apart and keep them in the same location for all conditions, 3) flex and extend trunks repeatedly in the sagittal plane as fast as can be done comfortably while keeping the transverse plane position dot between the target zone dots, 4) watch the dots at all times during testing, 5) if transverse plane position falls outside the target zone, a tone will sound and the trial will be repeated, and 6) move continuously until instructed to "relax." Data were collected up to 14 seconds for each experimental run.

Data Analysis: Performance Measures. Custom software developed in the Ohio State University Biodynamics Laboratory converted the electrical signal from each back monitor into trunk position, velocity, and acceleration. The software program graphically displayed trunk positions in each plane of the body separately and permitted each motion component to be independently analyzed throughout the exertion. The first entire cycle (flexion and extension) during each trial was considered a warm-up motion and was discarded for analysis purposes. The following four flexions were analyzed and averaged. This process was completed for each plane of the body. The analysis program computed the trunk motion characteristic variables discussed earlier.

The feature extraction from the continuous movement patterns required the following data processing. The middle three cycles of movements were interpolated and averaged into 128 data points. Thus, the data were normalized with respect to cycle time and permitted between-individual comparison. Data matrices consisted of the 171 columns (number of patients) and 128 rows (number of data points for each patient's continuous profile—i.e., position, velocity, and acceleration). The eigen value and eigen vectors of the correlation matrix of the patient data matrices were computed by singular value decomposition algorithm using MATLAB (MathWorks, Inc.

Natick, MA). The eigen vectors represent the principal patterns (bases), and the cumulative sum of eigen values reflect the amount of explained variability of the original data matrix. Using the original data matrices and the eigen vectors, the weighting coefficient matrices were computed. Inspection of eigen values indicated that the first five eigen vectors explained more than 97% of the variability of the original data. The first 10 weighting coefficients were used to reconstruct the original movement profiles. Using the eigen vectors extracted from the patients' data matrices, the weighting coefficients for normal subjects also were computed. Thus, because the coefficients of both healthy subjects and patients had the same bases, the continuous patterns of motion, with a significant reduction in the dimension of the original data (from 128 data points to 10 coefficients), could be represented. A more detailed description of the method is provided in Marras et al.[21] and Parnianpour et al.[33]

Data Analysis: Analyses. The trunk motion characteristics of the healthy and LBD groups were characterized through descriptive statistics. Next, each of the trunk motion variables measured by the LMM were normalized with respect to the gender and age values from the database of healthy subjects.

Eight variable motion component models were created that included normalized position, velocity, and acceleration component measures in the sagittal, frontal, and transverse planes. Thus, the free-dynamic nature of the trunk motion was evaluated in three-dimensional space. Subject classification was evaluated using four methods. Different methods were used because the various methods varied in their ability to evaluate the interactions between the variables. These evaluation techniques included: 1) classification and regression trees, 2) classification using splines (ordinary spline), 3) conventional discriminant analysis, and 4) a modified classification using splines technique. Classification and regression trees is a nonparametric classification technique[7,8] that uses a binary tree approach to partition the measurement space. Classification using splines is a recent statistical method and is similar to the neural network method. However, it is noniterative and based on additive regression. It permits nonrigid boundaries between classifications. Classification using splines also is much faster than neural networks.[6] Discriminant analysis uses linear combinations of variables, but also is capable of considering a limited amount of variable interaction. Finally, the modified classification using splines method was developed by Bose[5] and differs from the other methods in that it does not assume additivity of the motion components and can account for a greater degree of interaction between variables in its classification decisions. Thus, these four classification techniques vary in terms of rigidity of classification boundaries and the amount of interaction they can accommodate in their analyses. The first two techniques consider the main effects of the eight motion component variables. The last two techniques permit interaction, but at different levels, with the modified classification using splines permitting the greatest amount of interaction consideration.

Misclassification error rates and cross-validation error were used as the measures of model success. A standard technique for testing the validity of a model is to apply the model to an independent test set. When an independent test-set sample is not available, a method's performance should not be judged by looking only at the re-substitution error (the misclassification error for the training set) because that will result in overfitting. An acceptable alternative technique is cross-validation, where the data are divided into random subgroups. In this procedure, each subgroup is kept aside as a test set one at a time and the remaining data are used to train the method. The misclassification errors for the subgroups that are used as test sets are recorded and pooled. The resulting cross-validation error is a more reliable error estimate than the re-substitution error.[8] Finally, a small independent data set (37 subjects not part of the original data set) was used to independently test the classification model that distinguished between healthy subjects and LBD patients.

■ Results

Quantification of LBD

As expected, trunk angular ROM, velocity, and acceleration in the sagittal plane decreased for all subjects as the test condition became more asymmetric. Table 4 shows some descriptive statistics of the sagittal plane ROM, velocity, and acceleration features for the healthy subjects as well as for the 10 LBD groups. Only variables used later in the classification models are shown in this table. However, similar descriptive statistics were derived for all of the performance measures. Compared with the normative group, the ability to perform the various asymmetric conditions and the magnitude of the performance measures (Table 4) were significantly reduced in the LBD group. The greatest differences between the healthy and LBD categories were related to measures of the higher order derivatives of motion (i.e., velocity and acceleration). For example, the mean sagittal plane ROM between the healthy and LBD groups under the symmetric (zero) condition differed by only 5°. However, sagittal plane extension velocity and acceleration measures were reduced by a mean of 49 deg/sec and 251 deg/sec^2, respectively, in the LBD group.

To determine whether trunk motion can serve as a measure of LBD, it was necessary to evaluate how trunk motion may be affected by LBD status and other factors, such as age and gender. Therefore, the trunk motion components were tested for significant differences as a function of LBD status (LBD vs. normal), gender, and age. Multivariate and univariate analyses of variances indicated that all velocity and acceleration components differed significantly as a function of LBD and age (at the 0.001 level of significance). Range of motion was found to be significant only as a function of gender, age, and their interaction in the sagittal plane. It did not differ as a function of LBD status. Sagittal plane trunk angular velocity and acceleration also varied as a function of gender (at the 0.01 level of significance). Few significant interactions of these variables were identified at either level of significance. These findings suggest that the higher level derivatives of motion (velocity and acceleration) are much more sensitive measures of LBD than ROM, which did not differ between healthy subjects and patients with LBDs. In addition, we have shown that only the measured motion characteristics of

Table 4. Mean (Standard Deviation) of Selected Trunk Motion Features for Healthy Subjects and Patients With LBD

	Category										
Motion Parameter	Healthy	Quebec 1	Quebec 2	Quebec 3	Spondylolisthesis	HNP >3	HNP ≤3	Stenosis	Quebec 9.2	Nonorganic	Quebec 11
Sum of ability across all five conditions (no. of conditions performed)	4.7 (0.7)	3.2 (1.0)	2.7 (1.1)	2.6 (1.0)	3.9 (1.2)	2.5 (1.4)	3.5 (1.6)	1.6 (0.8)	2.0 (1.6)	1.7 (1.2)	3.8 (1.6)
Twisting range (deg)	58 (6)	43 (14)	35 (14)	31 (16)	49 (15)	34 (15)	47 (15)	25 (11)	27 (17)	19 (9)	51 (23)
Sagittal range of motion at zero condition (deg)	36 (15)	37 (15)	29 (16)	30 (13)	40 (12)	30 (11)	29 (11)	27 (12)	27 (13)	28 (14)	33 (17)
Sagittal flexion velocity at zero condition (deg/sec)	92 (49)	60 (36)	42 (25)	34 (21)	69 (38)	40 (30)	52 (30)	33 (19)	28 (20)	31 (19)	68 (41)
Sagittal extension velocity at zero condition (deg/sec)	96 (48)	61 (36)	47 (29)	33 (19)	70 (34)	45 (32)	55 (30)	35 (19)	30 (15)	32 (22)	66 (40)
Sagittal flexion acceleration at zero condition (deg/sec^2)	404 (245)	208 (167)	139 (92)	106 (71)	281 (232)	135 (131)	189 (116)	111 (93)	82 (50)	85 (54)	269 (183)
Sagittal extension acceleration at zero condition (deg/sec^2)	414 (254)	208 (141)	149 (97)	100 (65)	292 (203)	138 (109)	185 (112)	117 (127)	90 (54)	99 (79)	257 (187)
Lateral range at zero condition (deg)	3.3 (2.7)	3.6 (1.9)	3.2 (1.8)	3.3 (2.0)	3.1 (1.2)	3.3 (2.2)	3.0 (2.0)	3.0 (1.9)	2.7 (2.1)	3.1 (1.1)	5.7 (3.6)
Lateral right velocity at zero condition (deg/sec)	12 (9.9)	9.0 (7.2)	6.9 (3.8)	6.1 (5.0)	7.5 (3.1)	6.4 (4.0)	7.4 (5.0)	5.4 (4.5)	4.6 (3.7)	5.2 (2.4)	14 (8.3)

HNP = herniated nucleus pulposus.

a subject need be adjusted (where significant) for the influences of the age and gender to quantify performance relative to the normative group.

The mean values (and the associated standard deviations) needed to normalize the trunk motion variables (for age and gender) used in the classification models are shown in Table 5, except for the weighting coefficients for the continuous variables (available on request). This normalization of the motion characteristics was performed to characterize the various LBD status measures (i.e., ROM, velocity, acceleration) in common terms. This normalization process permits the extent of an LBD to be quantitatively described by characterizing the patient's trunk motion characteristics relative to the expected trunk motion characteristics of the healthy group. Thus, LBDs can be described in terms of the percent of the normative group's motion characteristics, as shown in Table 6, for the variables used in the classification models. For example, patients in the HNP classification (>3) produced 78% of the ROM of the healthy group's sagittal ROM at the zero condition once matched for age and gender relative to the healthy

Table 5. Mean (Standard Deviation) Trunk Motion Features of the Healthy Subjects Shown As a Function of Gender and Age

			Age									
			Male					Female				
Plane	Direction	Motion Variable	20s	30s	40s	50s	60s	20s	30s	40s	50s	60s
Sagittal	Flexion	Range (deg)	38.71 (41.41)	41.47 (13.57)	42.75 (14.35)	42.76 (16.58)	37.60 (15.54)	38.64 (17.04)	31.41 (12.82)	29.28 (10.61)	26.47 (7.72)	23.88 (9.46)
		Velocity (deg/sec)	104.12 (51.98)	113.88 (49.86)	107.53 (47.15)	101.75 (49.38)	80.25 (45.51)	100.02 (53.74)	82.34 (37.71)	72.45 (28.73)	61.62 (19.54)	47.91 (15.87)
	Extension	Velocity (deg/sec)	106.54 (48.09)	120.94 (53.82)	114.84 (44.01)	105.16 (46.26)	81.99 (42.88)	104.50 (53.43)	90.95 (39.96)	78.31 (29.35)	67.79 (22.14)	49.64 (18.38)
	Flexion	Acceleration (deg/sec^2)	475.49 (250.44)	541.90 (287.85)	473.56 (248.38)	425.40 (222.40)	299.02 (181.32)	435.59 (270.85)	354.86 (175.65)	335.70 (144.80)	257.09 (117.98)	194.71 (72.27)
	Extension	Acceleration (deg/sec^2)	490.93 (269.25)	552.06 (302.13)	493.27 (248.04)	417.55 (206.49)	322.76 (264.20)	445.10 (248.90)	373.01 (187.90)	318.66 (163.54)	291.78 (146.52)	188.36 (90.72)
Lateral	Right	Range (deg)	3.72 (3.22)	4.25 (3.70)	3.14 (2.55)	3.74 (2.77)	2.69 (1.59)	2.95 (2.05)	3.22 (3.56)	2.69 (1.46)	2.87 (1.61)	2.67 (1.86)
		Velocity (deg/sec)	13.29 (10.61)	15.49 (13.66)	10.72 (7.95)	12.73 (8.02)	9.44 (8.22)	12.72 (12.37)	11.53 (11.58)	10.96 (7.07)	9.83 (4.83)	8.20 (4.57

Any motion features of LBD patients can be normalized by dividing the measured value by the age- and gender-matched mean value reported in this table.

Table 6. Normalized Patient Performance for Selected Motion Characteristics as a Function of LBD Classification

Motion Parameter	Categories									
	Quebec 1	Quebec 2	Quebec 3	Spondylolisthesis	HNP >3	HNP ≤3	Stenosis	Quebec 9.2	Nonorganic	Quebec 11
Sum of ability across all five conditions (no. of conditions performed)	66	54	52	80	50	74	32	42	34	78
Twisting range of motion	75	60	55	85	60	80	46	46	32	85
Sagittal range of motion at zero condition	100	80	82	100	78	81	85	74	72	92
Sagittal flexion velocity at zero condition	65	44	38	70	41	53	46	30	32	72
Sagittal extension velocity at zero condition	65	46	34	67	43	43	48	31	31	66
Sagittal flexion acceleration at zero condition	51	33	27	65	31	43	39	20	19	65
Sagittal extension acceleration at zero condition	52	34	24	64	31	40	38	22	21	60
Lateral range at zero condition	100	100	97	90	98	88	100	85	88	180
Lateral right velocity at zero condition	79	56	51	59	51	60	56	41	42	111
First coefficient of the position profile	100	61	39	90	60	68	56	27	38	56
First coefficient of the velocity profile	64	43	30	65	40	51	26	21	23	57
First coefficient of the acceleration profile	46	29	17	52	27	38	14	11	13	50

Values indicate the percentage of the mean normal group's performance.
HNP = herniated nucleus pulposus.

group. On the other hand, the sagittal plane extension velocity and acceleration at the zero condition were 43% and 31% of the healthy group's age- and gender-adjusted values, respectively.

Classification of LBD

The normalized trunk motion characteristics were used as a basis for classifying the 510 subjects who participated in this experiment into the various healthy and

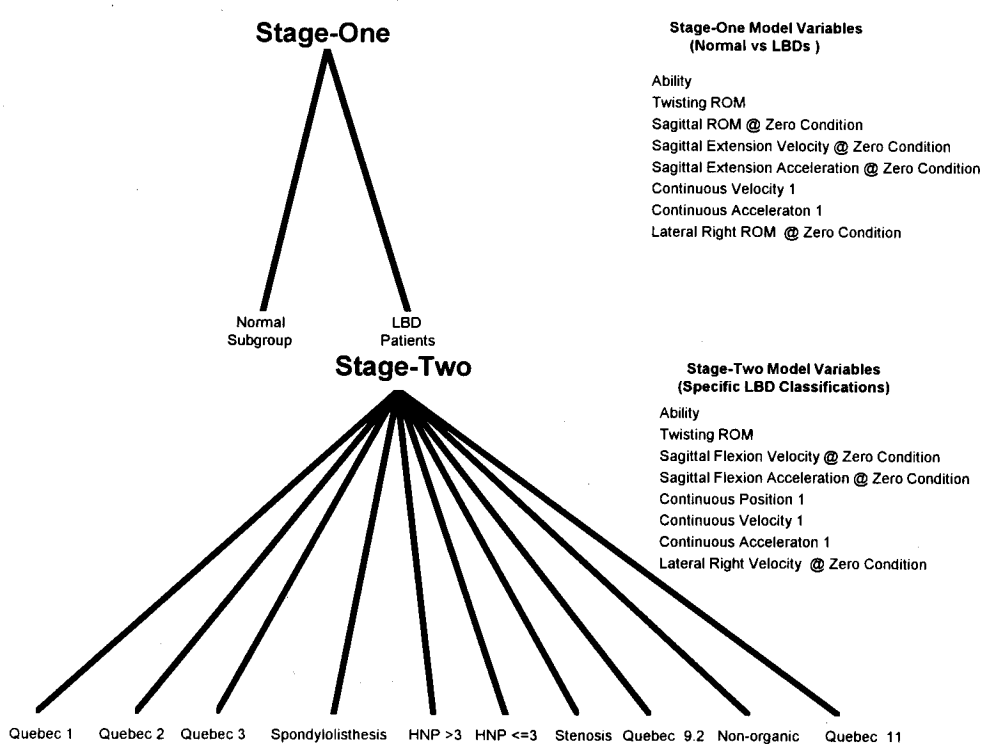

Figure 2. The stage two model used to categorize patients with LBDs. The stage one model separates healthy subjects from LBD patients (as a group), whereas the stage two model categorizes the LBD patients into one of 10 LBD classifications.

Table 7. Stage One (LBD vs. Healthy) Classification and Cross Validation Error Shown as a Function of Classification Method

	Classification and Regression Trees	Classification Using Splines	Discrimination Function	Modified Classification Using Splines
Original data	7.2%	6.3%	8.6%	4.9%
Cross validation of original data	9.0%	11.8%	11.0%	5.5%

LBD groups. As shown in Figure 2, a two-stage analysis was performed to accomplish this goal. We assumed that only highly repeatable measures of trunk motion could be used in the model. Two models were developed based on biomechanical plausibility, stepwise discriminant analysis, and numerous simulations. The eight-variable model shown in stage one of Figure 2 distinguishes well between healthy subjects and LBD patients.

The classification and cross-validation results of the Classification and Regression Trees, CUS, discriminant analysis, and MCUS methods for the stage one objective (LBD patients vs. normal subjects) are shown in Table 7. Most of the methods tested achieved a high degree of accuracy in classifying healthy subjects versus patients. However, the MCUS method resulted in slightly better (lower) classification and cross-validation error.

The stage two model attempted to classify the LBD patients into specific diagnostic categories. The variables employed by this model are shown in Figure 2. Model performance is shown in Table 8 as a function of the various classification methods. Only the MCUS method could reasonably classify the patients into the appropriate categories when both classification and cross-validation measures were considered. This classification method was able to correctly classify over 99% of the patients in the original (training) data set and misclassified only one patient out of 171. The MCUS technique was the only method that also produced a reasonable cross-validation measure. About 30% of the patients were misclassified in this cross-validation. Table 9 shows the sensitivity and specificity for the cross-validation measure. Specificity was excellent, with an average over the 10 categories of higher than 96%. Sensitivity was lower, with an average of 69%. Table 10 shows the cross-validation classification matrix for stage two. This table shows that overall cross-validation classification performance varied from 55% to 88%, with the worst misclassification cell miscategorizing only three patients. In addition, 20 of the 35 misclassification cells involved the misclassification of only one patient.

■ Discussion

Three important issues have been addressed in this study. First, through the repeatability study, we found that the trunk motion characteristics examined were largely highly repeatable. Cronbach's correlation coefficients were used to investigate repeatability because they are more appropriate for time-indexed data such as ours. The Cronbach's correlation coefficients indicated there was excellent repeatability and reliability, particularly for the motion components in the zero (symmetric) condition. All Cronbach's correlation coefficients in this condition were 0.88 or greater in the sagittal and frontal planes. In fact, all Cronbach's correlation coefficients for the trunk angular velocity and acceleration measures were 0.91 or greater, indicating that the higher order derivatives or motion (velocity and acceleration) were the most repeatable measures. All sagittal plane motion components also exhibited excellent repeatability (Cronbach's correlation coefficient of 0.9 or greater) in the asymmetric (15° and 30°) testing conditions. The remaining frontal plane motion Cronbach's correlation coefficients were for the most part much lower, indicating that frontal plane repeatability was much more consistent in the zero testing condition compared with the asymmetric testing conditions.

The continuous motion measures were evaluated only in the sagittal plane. These were found to be most repeatable when the first four coefficients of velocity and acceleration were considered. All but two of the 10 acceleration coefficients also yielded acceptable Cronbach's correlation coefficients. Collectively, these results indicate that measuring free dynamic motions under these unloaded (no external resistance) conditions produces many highly repeatable motion components. It has been recommended by Nelson and Nestor[29] and Waddell et al[44] that only coefficients over 0.8 are acceptable as measures of repeatability. We found that in the sagittal and lateral planes of the trunk there were 39 variables with a coefficient of 0.9 or greater, indicating

Table 8. Stage Two (Specific LBD Categories) Classification and Cross Validation Error Shown as a Function of Classification Method

	Classification and Regression Trees	Classification Using Splines	Discrimination Function	Modified Classification Using Splines
Original data	76.6%	15.8%	34.9%	0.6%
Cross validation of original data	78.4%	75.4%	84.3%	30.9%

Table 9. Specificity and Sensitivity of Modified Classification Using Splines Cross Validation Analysis Results

Category	Specificity (%)	Sensitivity (%)
Quebec 1	98	88
Quebec 2	97	65
Quebec 3	97	65
Spondylolisthesis	99	75
Herniated disc pain >3	91	73
Herniated disc pain ≤3	99	83
Stenosis	94	61
Quebec 9.2	96	64
Nonorganic	94	59
Quebec 11	99	55

that these motion measures account for over 80% of the variance between testing sessions. Thus, many reliable motion-related variables are available for consideration in the quantification and classification models.

The second issue addressed was the quantification of LBDs. Because we established that many repeatable motion components can be considered measures of ability, we could use this information to quantify the status of an LBD patient. We have determined that once trunk motion components are adjusted for age (and in some cases gender), they can be compared with the normative database and used as a quantitative measure of LBD. These repeatable trunk motion measures are able to quantify the functional limitations associated with various LBD disease states in common terms (percent of expected normal ability) and can serve as a measure of the extent of the disorder and as a measure of rehabilitative progress.

The final issue addressed was the classification of LBDs. We have developed a two-stage model that employs reliable trunk motion measures, reflecting the three-dimensional dynamic action of the trunk in a MCUS system, to successfully classify subjects into 10 anatomic-and symptom-based LBD groups. The first stage of the model was used to distinguish LBD patients from healthy subjects. Only the zero degree test condition, along with a measure of twisting range and ability, was needed to accurately identify general LBD. This model was able to correctly identify 94% to 95% of our 510 healthy subjects and LBD patients. A small independent data set (different from the original data set) of 16 healthy subjects and 21 LBD patients was used to further explore the stage one classification validity. The stage one model was able to correctly classify 90% of this small validation group, indicating that the model holds great promise for correctly identifying LBD patients. Further independent validation tests are necessary to fully validate the model.

The success of the stage one model in identifying LBD patients is particularly impressive when compared with others who have attempted to identify LBD patients using other means. DeLuca,[10] using spectral measures of electromyography, was able to correctly identify only 84% of healthy subjects and 91% of LBD patients,

Table 10. Classification Matrix for the Stage Two Modified Classification Using Splines Cross Validation Results Showing the Number of Subjects and Percentage of the Subject Population Classified Into Each Category

	Predicted Group Membership										
Actual Group Membership	Quebec 1	Quebec 2	Quebec 3	Spondy-lolisthesis	HNP >3	HNP ≤3	Stenosis	Quebec 9.2	Nonorganic	Quebec 11	Totals
Quebec 1	**14**	0	0	0	0	0	1	0	1	0	16
	88%	0	0	0	0	0	6%	0	6%	0	
Quebec 2	1	**11**	0	0	2	0	1	1	0	1	17
	6%	**65%**	0	0	12%	0	6%	6%	0	6%	
Quebec 3	0	0	**11**	0	2	0	2	1	1	0	17
	0	0	**65%**	0	12%	0	12%	6%	6%	0	
Spondylolisthesis	1	0	0	**12%**	1	0	1	0	1	0	16
	6%	0	0	**75%**	6%	0	6%	0	6%	0	
HNP >3	1	3	1*	0	**22**	0	3	0	0	0	30
	3%	10%	3%	0	**73%**	0	10%	0	0	0	
HNP ≤3	0	0	0	0	0	**10**	0	1	0	1	12
	0	0	0	0	0	**83%**	0	8%	0	8%	
Stenosis	0	0	2	1	3	0	**16**	2	2	0	26
	0	0	8%	4%	11%	0	**61%**	8%	8%	0	
Quebec 9.2	0	0	0	0	2	0	0	**7**	2	0	11
	0	0	0	0	18%	0	0	**64%**	18%	0	
Nonorganic	0	1	2	0	1	0	1	2	**10**	0	17
	0	6%	12%	0	6%	0	6%	12%	**59%**	0	
Quebec 11	0	0	0	0	2	2	0	0	0	**5**	9
	0	0	0	0	22%	22%	0	0	0	**55%**	
											171

Bold numbers along the diagonal indicate correct classifications.
The percentage classified is rounded to the nearest whole number and may not sum to 100.
HNP = herniated nucleus pulposus.
* The location of the only misclassification in the original data.

although the results were not cross-validated. The subject population used in this study was extremely small compared with our study. Although his method, as well as ours, attempts to evaluate the status of the musculoskeletal system, we believe that our method is successful because it considers performance in association with dynamic motion, whereas spectral electromyography must be performed under static conditions. As shown in this study, dynamic measures are very repeatable. Klein et al[18] used discriminant analysis to classify LBD as a function of ROM, isometric extension strength, and spectral electromyography. Sensitivity was found to be 66% and specificity was 71%. Also, numerous studies reported in the literature have failed to show differences between LBD patients and healthy subjects.[2,3,10,25,28,31,35,41] Because most of these studies were based on ROM, we believe that such measures do not hold much promise for classification purposes. Finally, Newton et al[30] and Masset[25] used various measures of isometric as well as dynamic strength to distinguish between healthy subjects and LBD patients. These measures also resulted in specificity and sensitivity measures that were not as robust as our stage one model results.

The stage-two portion of our model results in the only model (to our knowledge) able to quantifiably classify subjects into specific LBD categories. This model uses six variables based on the zero degree (symmetric) testing condition and two variables related to the ability to twist the trunk. This model also used the MCUS technique. The error rate of the model was an impressive 0.6%. Cross-validation studies have shown that expected validation also is acceptable, with a cross-validation error of 30.9%. Hence, we expect that in an independent validation study, about 70% of patients could be correctly classified using this model. The cross-validation sensitivity and specificity of the stage-two model was superior compared with existing imaging techniques.

It has been estimated that imaging techniques can identify the source of an LBD less than 20% of the time.[27] The classification matrix showing the classification performance of our MCUS model (Table 8) indicates that even a herniated disc, one of the more elusive categories, was classified correctly between 73% and 83% of the time, depending on pain level. We believe that our model is successful where others are not for several reasons. First, we used model components that were sensitive to musculoskeletal trunk status and were highly repeatable. Second, the spline methods are able to account for nonlinear boundaries between groups. For example, Figure 3 shows two of the stage one model variables, with the boundaries defined by discriminant analysis (Figure 3A) and the MCUS method (Figure 3B). The spline method can account for significantly more nonlinearities. This becomes particularly important when considering that the actual stage one model has eight variables and this technique could more accurately

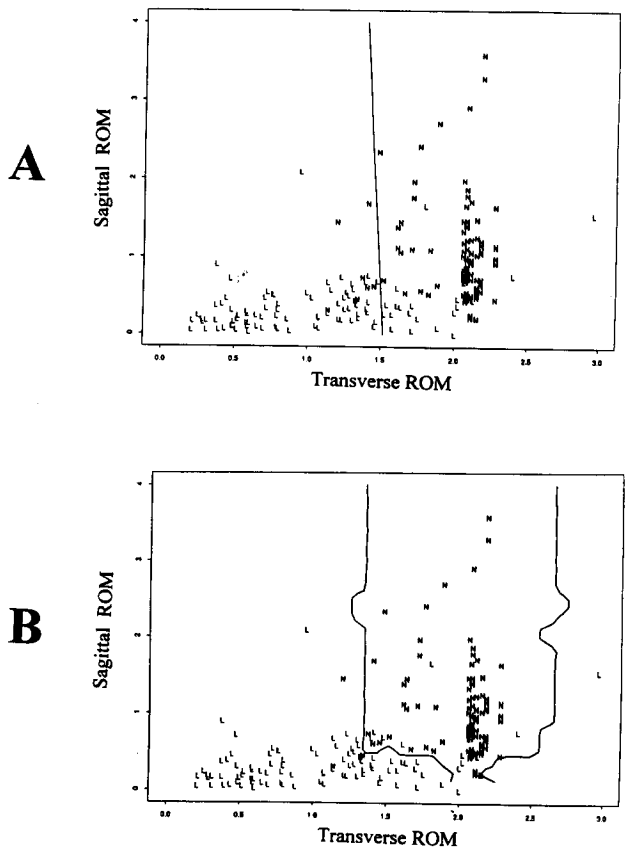

Figure 3. A representation of how different classification methods separate LBD patients (L) and healthy subjects (N) as a function of two motion variables (transverse ROM and sagittal ROM). Linear discriminant analysis (**A**) constructs a linear boundary and thus misclassifies a large number of patients as healthy, while the MCUS (**B**) generates complex nonlinear boundaries that minimize the misclassification. These boundaries are much more complex (and cannot be represented here) in the eight-variable models.

describe the complex trends found at the boundaries. Third, we were able to account for the specific interactions associated with three-dimensional motion using the MCUS technique. This technique permits us to not only observe general measures of velocity or acceleration, as other techniques can do, but the interaction permits us to account for acceleration at a specific velocity as a patient moves through a trunk-specific angle.

We have found that accounting for interactions is critical in the stage two classification. This adjustment improves model cross-validation by an average of 48% compared with classification methods that cannot account for this high degree of interaction between motion components. Thus, we can conclude from this study that unique patterns of ROM, velocity, and acceleration or "motion signatures" are associated with various LBD classifications, and examination of these interactive patterns (compared with examination of ROM, velocity, or acceleration independently) accentuates the differences between LBD categories. As an example, Figures 4A–C show the continuous ROM, velocity, and acceleration

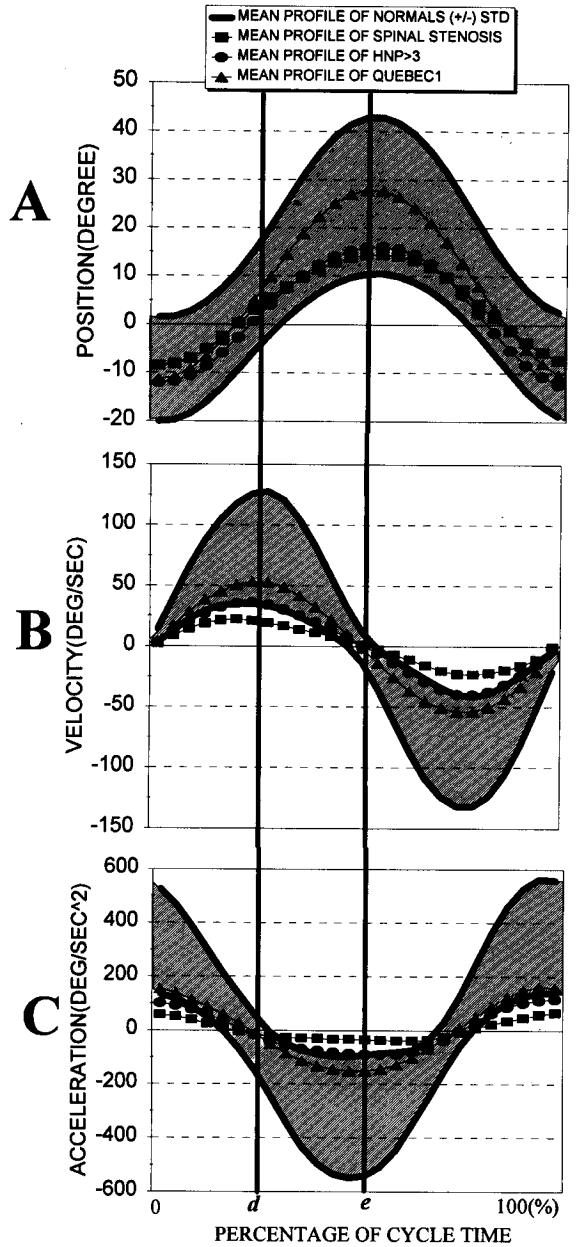

Figure 4. (**A**) Range of motion, (**B**) angular velocity, and (**C**) angular acceleration of the healthy group (means ± 1 SD; shaded) compared with the mean profiles of the spinal stenosis, HNP >3, and Quebec 1 groups. By observing the combined performance among these three measures at specific points in time (line d or e), an appreciation for the interactive nature of LBDs can be gained. Note how the relative position of each LBD changes relative to the healthy group between the three measures at different points in time.

(±1 SD) activity, respectively, for the healthy group (shaded area) compared with the means of the Quebec 1, spinal stenosis, and HNP >3 groups. By simultaneously comparing the instantaneous ROM, velocity, and acceleration at points throughout the cycle (indicated by vertical lines through all three figures), dramatically different combinations (interactions) of the three motion variables are evident. The MCUS is sensitive to these types or differences and to higher order interactions. These analytical models could not have been developed without quantitative measures of three-dimensional dynamic performance.

Like other sophisticated methods such as the neural network method, the mathematical expressions for the final model used by the spline methods are quite complex because they consist of spline functions involving interactions. Therefore, we have reported the original variables used in the final model (Figure 2). For future classifications, the measurements can be fed into the classifier, which will return the predicted class for the subject. The codes for these programs are available on request.

Basis of Trunk Motion Changes

Although the present study was not designed to explore the source of the trunk motion changes associated with an LBD, we can speculate about how these changes might occur. The trunk motions examined in this study may be a result of biomechanical as well as learned or cognitive processes. Many specialists in human gait can gain insight into the nature of a gait disorder by examining motion changes during walking. We believe that our motion components represent similar types of biomechanical events that we have been able to precisely quantify. Biomechanically, changes in trunk motion characteristics (compared with a healthy group) may reflect changes in the coordinated recruitment of the neuromuscular system. Increased co-activation could stiffen the trunk's musculoskeletal system and significantly slow trunk velocity and acceleration characteristics.[1] Changes in trunk motion characteristics also can signal sensitivities to tissue loading. Sudden increases or decreases in acceleration at a particular point throughout a movement also could indicate a biomechanical response to tissue sensitivity. Because our model can account for such interactions, we believe that some of the observed results indeed may reflect such tissue sensitivities. Unique changes in motion component interactions also may reflect abnormalities in the structures of the spine. We suspect that changes in spine structural integrity and sensory and proprioceptive pathways may result in unique combinations of motion components as various points in space are passed. Again, our model can account for sensitivities to such interactions.

Why does this free-dynamic technique of measuring motion assessment offer so much more information about the musculoskeletal system compared with traditional strength-based motion measurement systems? We believe that because resistance or loads are imposed on the spine in these strength-based systems, they may mask many of the subtle, well developed motion characteristics we can monitor by testing an unloaded trunk for three-dimensional motion characteristics. We also believe that measuring trunk motion by any means with similar system resolution (i.e. video, infrared, magnetic,

etc.) under unloaded free dynamic conditions would produce similar results.

These results also may reflect cognitive processes as well as biomechanical processes. Cognitive processes such as learned guarding behavior or automaticity develop in response to pain sensitivities or because of precautionary behavior associated with hypersensitivity to pain. Wolf et al[45,46] postulated that compensatory postural abnormal neuromuscular patterns (such as guarding) that develop over time may alter the normal neuromuscular function that will affect trunk motion characteristics. Our model may have the potential to identify such unique behavior, although we did not test that hypothesis here.

Practical Uses of the Model

Perhaps the greatest benefit of this model is that it could be used in conjunction with existing techniques to enhance assessment of LBDs. For example, this model could be used as a screening tool to narrow the range of possible LBD classifications. Then, based on model predictions of probabilities associated with specific classifications (classification matrix shown in Table 10), the physician could prioritize requests for specific tests and procedures that may further validate the diagnosis.

Our model has shown that under clinical circumstances it would not be necessary to test patients under all of the trunk asymmetry conditions. This study has shown that excellent predictions of classification can be gained by studying the three-dimensional trunk motion components at the zero condition, along with an indication of twisting motion range and ability to flex in deviated twisting positions. Neither the stage one nor stage two model of this study used the motion components associated with the 15° or 30° testing conditions, even though many of these variables are highly repeatable. Thus, practical usage of this technology may require a relatively quick and efficient test to assess LBD.

Recovery Index

Functional quantification of the patients is crucial for optimizing conservative treatment. Such quantification can sharpen the clinician's understanding of the functional deficits and help identify the appropriate dimensions of performance that need the greatest attention, (i.e., a patient who has adequate range of motion but who has only 50% of normative extension velocity). The functional deficits are time dependent and should be updated over the course of the rehabilitation. The strength and motion parameters are psychophysical measures and as such represent the patient's behavior in terms of what the patient is able to perform given the associated pain or disease. The outcome of these performances will depend on pain inhibition, fear avoidance,[44] psychological distress,[42] and illness behavior,[9,44] in addition to physical or sensory disorder. Thus, dynamic motion characteristics may provide sensitive outcome measures of patient recovery in multidisciplinary rehabilitation programs.[16]

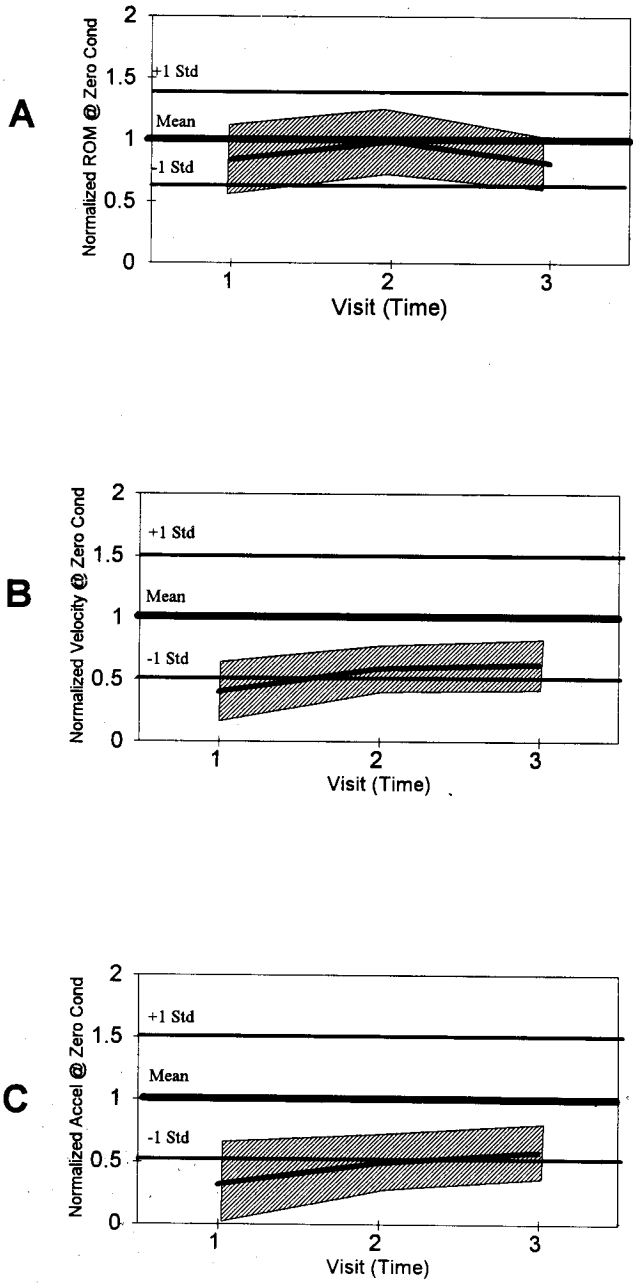

Figure 5. (A) Range of motion, (B) extension velocity, and (C) extension acceleration of 13 patients with LBD (means ± 1 SD; shaded) compared with the healthy group performance (means ± 1 SD) longitudinally over three office visits. Note that recovery occurs sequentially. Range of motion returns to normal range first, followed by velocity and finally acceleration.

To test this hypothesis, the present study also collected preliminary observations on some LBD patients longitudinally through the course of the LBD so we could explore the prognosis value of the dynamic parameters of motion. Thirteen LBD patients were tested during three visits to their physician over the course of their disorder. We observed that LBD recovery occurred

in a specific order. The normalized performance of these LBD patients relative to the healthy group's sagittal ROM, extension velocity, and accelerations are shown in Figures 5A–C, respectively, for the zero test condition. Seventy-seven percent of patients had ROM within the normal range (within the threshold defined as the mean ± 1 SD of the healthy group) in the initial visit, whereas only 31% and 8% of the patients' velocities and accelerations, respectively, were within the normal range.

We observed that patient recovery can be assessed by the improvement in performance parameters during the second and third visit. For example, by the third visit, 85% of the patients' ROM had returned to the normal range, whereas 54% and 38% of the velocity and acceleration measures, respectively, were within the normal range by the third office visit. This indicates that recovery initially occurs in terms of ROM. However, velocity and acceleration characteristics return to normal much later during the recovery process. Thus, we observed that the rate of improvement can be characterized more via a return to a normal range of the dynamic parameters compared with ROM. The functional restoration may be a function of reduction in the inhibitory afferent or efferent signals that influence the control strategies of trunk movements. In addition, it can be argued that the dynamic parameters are more sensitive in portraying changes in the functional state of LBD patients.

Limitations

Although we have demonstrated that trunk motions may serve as a quantitative measure of disability, this concept is in its infancy and requires more experimental research before it evolves into a more mature measure. A major complication is the tremendous complexity of the spine. The large number of degrees of freedoms in the passive spine, in addition to numerous muscles that span each motion segment, allow the central nervous system numerous possible motions. Thus, the kinematic and kinetic redundancies of the spine may limit the ability to correctly specify the insulted tissue via motion analysis. However, we can accurately quantify the functional trunk performance compared with the normative database, regardless of the source and functional deficit.

Several limitations must be considered in evaluating the efficacy of our findings. First, this study represents an initial 6-year effort whose aim was to find an accurate means of quantifying and classifying LBD. For such a system to become common practice, a formal validation using a new, large independent data set is required. This validation is the goal of the next phase of this project. Although cross-validation is a statistically acceptable validation measure, a formal validation involving a much larger sample of LBD patients, compared with this "training" data set, is needed to ensure the model is accurate and sensitive. Our small (37 subject) independent data set provided a preliminary indication that the model can discriminate well between LBD and healthy subjects. However, the data set was too small for truly assessing the degree of accuracy in the stage one model or for attempting a stage two classification validity test. This study also indicated that the MCUS technique was the only one capable of reasonably distinguishing between LBD classifications in cross-validation testing. This technique uses the processed data from the CUS technique as its input. Thus, it may be possible that the cross-validation estimate of MCUS was biased toward optimality. Only a new independent data set can formally validate these findings.

Second, it is unclear how well this motion-based classification system would perform using patients from a typical practice who have not been prescreened for psychological factors. Third, we have only tested patients with chronic LBD. It is not known whether a motion-based classification system such as this would be successful when used for patients with acute LBD whose compensatory motion patterns may still be developing. During the acute phase of low back pain, the symptom generation and the state of stress and strain in the anatomic tissues are much more related than in the chronic phase of low back pain, when illness behavior could become an issue. We believe that it may work even better than with the chronic LBD patients used in this study because acute injury motion patterns would show less symptom magnification and less generalized trunk muscle deconditioning. This situation may increase the likelihood that the motion characteristics will be related to specific pain locations in the trunk. Recent imaging investigations[11–13,40] have suggested that specific patterns of movement among the motion segments in the cervical and lumbar spines of patients are present. However, noninvasive techniques would not permit intersegmental motion to be analyzed triaxially during the dynamic complex (asymmetrical) conditions tested here. Therefore, although our motion variables are more global, mostly reflecting the lumbar motion, the correct classification of 70% suggests that it also may partially reflect the specific patterns separating LBDs. In addition, similar dynamic motion parameters were able to predict the risk associated with industrial jobs.[22] We are merging these two databases to address the use of the ergonomics studies (quantification of the task demands) and the clinical functional capacity evaluation.

■ Conclusion

The current socioeconomic climate demands increased quality of healthcare delivery while maintaining costs because the present rapid growth in healthcare expenses cannot be sustained. As part of this effort, the need to quantify trunk performance was realized.[22,38] This need soon will grow to include quantification of the rehabilitation processes. However, quantification must include credible measures.[26] For healthcare costs to be curtailed,

clinicians must have sensitive and reliable tools for scientifically and critically evaluating the activities of the multidisciplinary rehabilitation team and their patients. We envision that the task of LBD management will consist of several stages—objectively measuring the present state of trunk performance, making a diagnosis, quantifying the functional deficits, planning a definite goal (target), selecting the optimal effective treatment (conservative or surgical), prescribing a quantifiable dose of therapeutic exercise, and providing feedback for positive reinforcement of progress and functional restoration with an operant conditioning behavioral approach.[14,19]

The present study has indicated that higher order trunk motion components can provide a tool to serve as such a reliable quantitative measure. We also have demonstrated that these measures can be used in valid models for classifying LBDs. Thus, this work contributes to the first three stages of the rehabilitation process. Future independent validation studies are needed to fully develop this approach.

Acknowledgment

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