Gait & Posture 30 (2009) 100–105

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Predicting outcomes of rectus femoris transfer surgery

Jeffrey A. Reinbolt [a,*], Melanie D. Fox [b], Michael H. Schwartz [c,d], Scott L. Delp [a,b]

[a] Department of Bioengineering, Stanford University, United States
[b] Department of Mechanical Engineering, Stanford University, United States
[c] Departments of Orthopaedic Surgery and Biomedical Engineering, University of Minnesota, United States
[d] Center for Gait and Motion Analysis, Gillette Children's Specialty Healthcare, United States

ARTICLE INFO

Article history:
Received 13 January 2009
Received in revised form 20 February 2009
Accepted 22 March 2009

Keywords:
Predicting outcomes
Rectus femoris transfer
Stiff knee gait
Cerebral palsy
Gait analysis

ABSTRACT

Rectus femoris transfer surgery is a common treatment for stiff knee gait in children with cerebral palsy. Unfortunately, the improvement in knee motion after surgery is inconsistent. There is great interest in understanding the causes of stiff knee gait and determining predictors of improved knee motion after surgery. This study demonstrates that it is possible to predict whether or not a patient's knee motion will improve following rectus femoris transfer surgery with greater than 80% accuracy. A predictive model was developed that requires only a few preoperative gait analysis measurements, already collected as a routine part of treatment planning. Our examination of 62 patients before and after rectus femoris transfer revealed that a combination of hip power, knee power, and knee flexion velocity at toe-off correctly predicted postoperative outcome for 80% of cases. With the addition of two more preoperative measurements, hip flexion and internal rotation, prediction accuracy increased to nearly 88%. Other combinations of preoperative gait analysis measurements also predicted outcomes with high accuracy. These results provide insight into factors related to positive outcomes and suggest that predictive models provide a valuable tool for determining indications for rectus femoris transfer.

1. Introduction

Stiff knee gait is one of the most common gait abnormalities in ambulatory children with cerebral palsy [1]. Stiff knee gait is a debilitating gait pathology in which knee motion is substantially diminished, and peak knee flexion in swing is delayed. Due to inadequate toe clearance, subjects with stiff knee gait frequently trip or adopt energy inefficient compensatory movements such as circumduction or vaulting [2].

Rectus femoris transfer surgery is a common treatment for stiff knee gait [3,4]. Over-activity of the rectus femoris muscle is considered the primary cause of limited knee flexion, and rectus femoris transfer surgery is intended to decrease the muscle's ability to extend the knee [3–5]. Three groups of studies have reported various degrees of average peak knee flexion improvement following rectus femoris transfer. The first group reported large average improvements between 12° and 26° [6–8]. The second group of studies reported small average improvements between 7° and 10° [3,6,9,10]. The third group of studies reported less positive average improvements related to swing phase peak knee flexion in some patients [10–14].

Outcomes of rectus femoris transfer surgeries to treat stiff knee gait are inconsistent, in part, due to insufficient understanding of predictors for positive outcomes. Sullivan et al. [15] used regression analysis to establish a relationship between preoperative and postoperative kinematics for 15 patients following rectus femoris transfer. Niiler et al. [16] used neural networks to make predictions of knee kinematics after rectus femoris transfer for a six-patient testing set with an 18-patient training set. Kay et al. [17] used regression analysis to determine factors related to postoperative gait velocity for 47 patients with cerebral palsy following a variety of surgical treatments. Goldberg et al. [18] used statistical analysis to determine factors correlated with improved postoperative knee flexion for 18 patients with stiff knee gait. Despite these studies, it remains unclear how to combine preoperative data to predict whether knee flexion will improve following rectus femoris transfer. At present, indications for rectus femoris transfer are based on qualitative observations of the patient's gait, physical examination of muscle tone, inspection of gait analysis measurements such as rectus femoris activity in early swing, and the experience of the clinical team. A better understanding of factors that predict outcomes is necessary to refine the clinical indications for rectus femoris transfer surgery.

* Corresponding author at: Clark Center, Room S-322, Stanford University, Mail Code 5450, 318 Campus Drive, Stanford, CA 94305-5450, United States. Tel.: +1 650 725 9486; fax: +1 650 724 1922.
E-mail address: reinbolt@stanford.edu (J.A. Reinbolt).

0966-6362/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.gaitpost.2009.03.008

This study used data mining techniques to predict outcomes of rectus femoris transfer surgery in treating stiff knee gait. Our first goal was to select a set of preoperative gait features that distinguished between good (*i.e.*, no longer stiff) and poor (*i.e.*, remaining stiff) postoperative outcomes. Our second goal was to determine which combinations of preoperative features best predicted postoperative outcomes. Identifying the best combinations of features to preoperatively categorize subjects with stiff knee gait provides an objective tool that complements the experience of the clinical team.

2. Methods

The subjects in this study had previously undergone gait analysis at Gillette Children's Specialty Healthcare, St. Paul, MN. Gait analysis data, including three-dimensional joint angles, moments, and powers, were recorded or computed as a routine part of treatment planning. Our inclusion criteria [18] required that each subject (i) subsequently underwent rectus femoris transfer surgery as a correctional treatment for stiff knee gait, (ii) was between six and 17 years of age prior to surgery, (iii) had not previously undergone a selective dorsal rhizotomy, and (iv) walked without orthoses or other assistance. Institutional approvals were obtained for retrospective analysis of each subject's preoperative and postoperative data.

Four gait parameters were used to determine whether a subject walked with stiff knee gait [18]: (i) peak knee flexion in swing phase (*e.g.*, [3,6]), (ii) knee range of motion in early swing [19], (iii) total knee range of motion (*e.g.*, [3,12]), and (iv) timing of peak knee flexion during swing phase (*e.g.*, [6,12]). A limb was classified as "stiff" if three or more of these measures were more than two standard deviations below (or above in the case of the timing of peak knee flexion) the average control value from able-bodied subjects matched for age, height, and weight. In subjects for whom both limbs met the stiff criteria, the limb that was stiffer was included. A group of 81 subjects met the inclusion criteria and were classified as stiff preoperatively.

The group of 81 subjects classified as stiff preoperatively was divided into two groups based on whether each subject walked with stiff knee gait postoperatively [18]. Nineteen subjects were classified as borderline cases postoperatively and excluded from further analysis. Thirty-one subjects were classified as not-stiff postoperatively (*i.e.*, one or none of the measures were indicative of stiff knee gait—five subjects had 0 indicative measures and 26 subjects had 1) and therefore categorized as exhibiting a "good outcome." Thirty-one subjects were classified as remaining stiff postoperatively (24 subjects had 3 indicative measures and seven subjects had all 4) and therefore categorized as exhibiting a "poor outcome." With equal numbers of good and poor outcomes, there is a 50% probability of correctly predicting the outcome of any one subject in this study without the addition of a predictive model.

Two sets of preoperative gait features distinguishing between the 31-subject good outcome group and the 31-subject poor outcome group were used. The first set of features was determined from the literature. The *literature-based* features consisted of five previously published features from the stiff limb associated with improvements in knee flexion: (i) knee flexion velocity at toe-off [18,20], (ii) average hip flexion moment in double support [18], (iii) average hip flexion moment in early swing [20,21], (iv) average knee extension moment in double support [18], and (v) average knee extension moment in early swing [20,22].

The second set of preoperative gait features distinguishing between the good and poor outcome groups was determined by a filtering method [23]. The *filter-based* features were chosen based on the discriminant power of the gait analysis data (*e.g.*, Fig. 1a) from the pelvis and stiff limb (*i.e.*, each joint angle, moment, and power) for the subject groups identified in this study. The two-sample *t*-test is a commonly used filter-type approach for feature selection (Fig. 1b) [24]. Given m measures of gait analysis data (*e.g.*, preoperative knee flexion angle) having n number of samples throughout the gait cycle, there were $m \times n$ unfiltered features available to distinguish between good and poor outcome groups. Features were ranked in order of significance by their two-sample *t*-test statistic. The entire set of features was filtered to a reduced set of 25 most significant features with the highest *t*-test statistics.

Linear discriminant analysis (LDA) was used to determine the linear combination of significant preoperative features that best predicted postoperative outcomes (Fig. 1c). The original LDA formulation [25] is a well-known method for classification, such as classifying good and poor outcome groups. For this study, good outcome was encoded as 0 and poor outcome encoded as 1 to correspond with the risk for poor outcome following surgery. Given a set of significant preoperative features, LDA computed coefficients for a linear function of these features that defined a boundary, encoded as 0.5, between good and poor outcome groups. This boundary was then used to predict postoperative outcomes. For example, suppose a subject's predicted dependent variable value was 0.1. This subject's predicted outcome would be "good" since 0.1 is closer to 0 (good) than 1 (poor).

Prediction performance was evaluated by the repeated hold-out method [26]. The entire set of subjects was randomly separated into two subsets, called the training set and the testing set. The training set contained 80% of subjects and the testing set 20%. The training set was used as input for computing the LDA model, while the testing set was "held-out" for subsequent validation. The LDA training results were used to predict postoperative outcomes of the testing set. The predictions were compared to the known postoperative outcomes for the testing set to compute the percentage of correct predictions. Performing this hold-out method

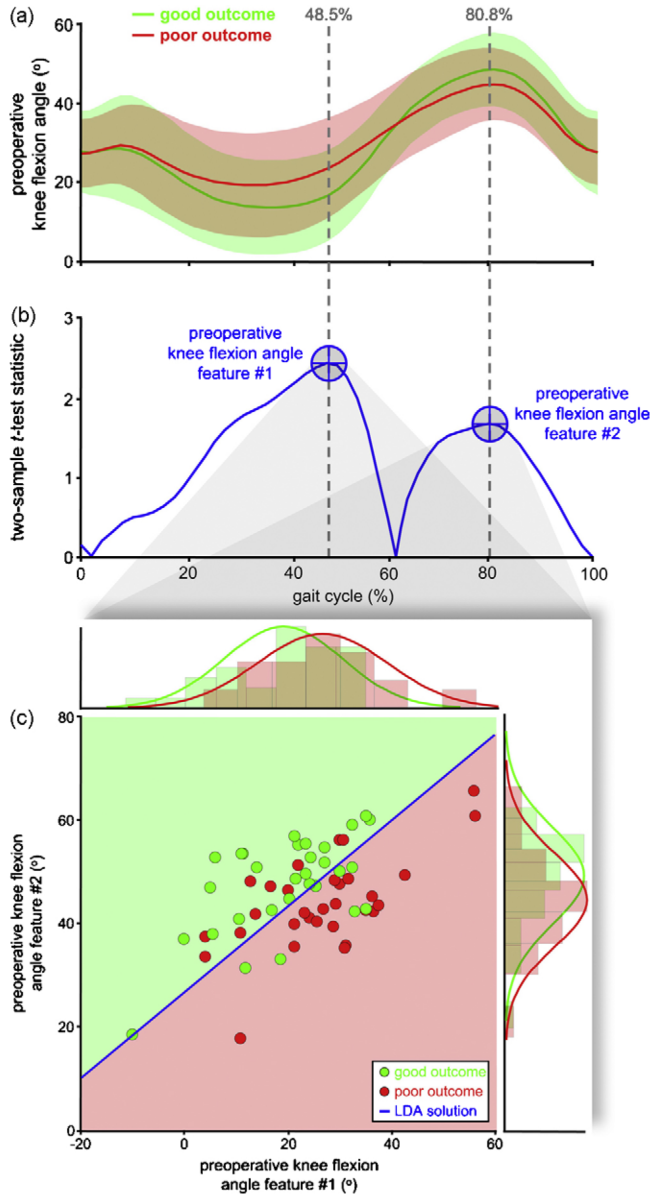

Fig. 1. Example of filter-based feature selection distinguishing between the good and poor outcome groups and linear discriminant analysis (LDA) resulting in the boundary line that best separates the different group classification regions. (a) The preoperative knee flexion data for each subject with stiff knee gait was divided into two groups based on whether each subject walked with stiff knee gait postoperatively. (b) The means and standard deviations for the good and poor outcome groups were used to determine the two-sample *t*-test statistic. The set of features available in the original data was filtered to a reduced set of significant features with the highest test statistics. (c) Linear discriminant analysis was performed for combinations of significant preoperative features. This discriminant analysis bears a strong resemblance to linear regression when the group classification is encoded as the dependent variable (*e.g.*, good outcome as 0 or poor outcome as 1) and the boundary represents a borderline case (*e.g.*, 0.5). Histograms of group distributions for individual features are shown on the top and right side of the scatter plot for comparison. Although this example is for knee flexion data, significant features were determined for all of the gait analysis data collected (*i.e.*, each joint angle, moment, and power). The 25 most significant features were determined (Fig. 2b). Linear discriminant analysis was performed for every combination of features to select the feature subsets with the highest percentage of correct predictions.

only once likely would have misrepresented the prediction performance. Therefore, the 20% hold-out method was repeated by randomly selecting a new training set for the LDA model and evaluating the predictions for a newly held-out testing set. This process was repeated until the mean percentage of correct predictions for all iterations converged to a constant value.

The best combinations of significant preoperative features were determined by a wrapper method [23] based on complete exploration of every feature subset with a maximum of five features. The complete method is the simplest wrapper-type approach for feature selection [24]. However, this approach is computationally intensive because LDA is performed for every combination of features to select the feature subset with the highest percentage of correct predictions. The binomial coefficient $\binom{n}{k}$ determines the number of different k-feature subsets that can be chosen from an n-feature set. More than $\sum_{k=1}^{30}\binom{30}{k} = 1.07$ billion different feature subsets are possible for our relatively small set of 30 features (*i.e.*, five literature-based and 25 filter-based features). To reduce computational intensity, the final subset size was limited to five or less features to maintain a reasonable $\sum_{k=1}^{5}\binom{30}{k} = 174,436$ subsets for the combination of all 30 features. In addition, we separately explored $\sum_{k=1}^{5}\binom{5}{k} = 31$ subsets chosen from the five literature-based features and $\sum_{k=1}^{5}\binom{25}{k} = 68,405$ subsets chosen from the 25 filter-based features. The percentage of correct outcome predictions was determined for each subset of significant preoperative features.

3. Results

Several combinations of preoperative features correctly predicted postoperative outcomes better than the actual 50% probability of the input data (Table 1). Given both literature-based (Fig. 2a) and filter-based features (Fig. 2b) meeting our first goal of selecting preoperative gait features that distinguish between good and poor postoperative outcomes, we achieved our second goal of determining which combinations of features best predict outcomes. The percentage of correct predictions was highest (87.9% correct) using a combination of hip flexion and hip power after initial contact (4.4% gait), knee power at peak knee extension in stance (40.7% gait), knee flexion velocity at toe-off (62.7 ± 3.5% gait), and hip internal rotation in early swing (71.4%

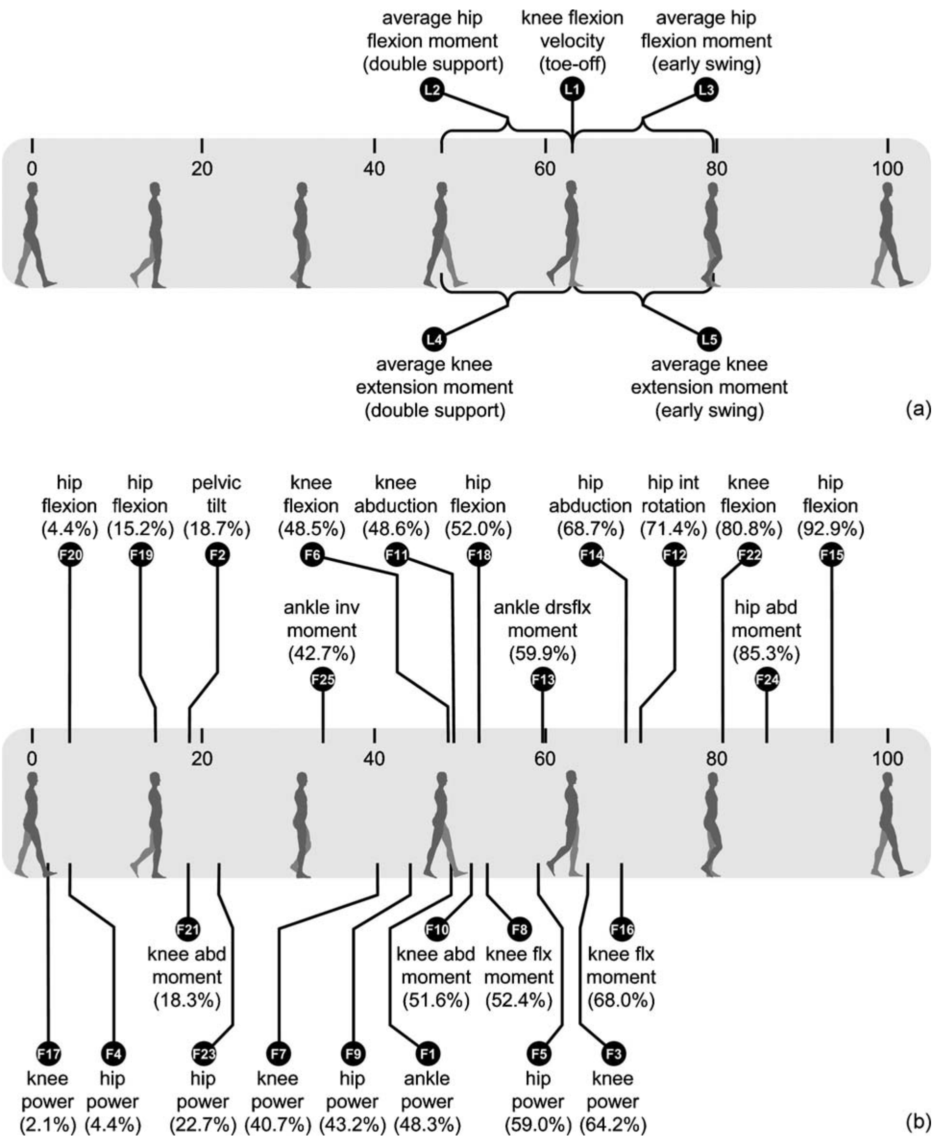

Fig. 2. The two sets of preoperative features distinguishing between the good and poor outcome groups. (a) The five preoperative literature-based features associated with improvements in knee flexion. Features are numbered in no particular order and shown at their corresponding locations during the gait cycle. For the subjects in this study, double support was from 47.9 ± 2.9% gait to 62.7 ± 3.5% gait and peak knee flexion occurred at 79.7 ± 5.1% gait. (b) The 25 most significant preoperative filter-based features distinguishing between the good and poor outcome groups that were determined by the two-sample t-test filtering method (Fig. 1a and b). Features are ranked in order of significance by their t-test statistics and shown at their corresponding locations during the gait cycle.

Table 1
Summary of the best combinations of three or less significant preoperative features and corresponding percentages of correct predictions.

Significant preoperative features (portion of gait cycle)	Combination	Correct prediction (%)
Literature-based features		
L1. Knee flexion velocity (toe-off)	L1–L2	**68.1**
L2. Average hip flexion moment (double support)	L1	67.8
L5. Average knee extension moment (early swing)	L1–L2–L5	66.4
Filter-based features		
F1. Ankle power (48.3%)	F2–F18–F22	**78.3**
F2. Pelvic tilt (18.7%)	F2–F18	74.1
F4. Hip power (4.4%)	F1	68.2
F18. Hip flexion (52.0%)		
F22. Knee flexion (80.8%)		
Combination of literature-based and filter-based significant features	L1–F2–F4	**81.9**
	L1–F2	77.2

gait). The percentage of correct predictions remained high (80.2% correct) using a subset combination of only three of these features, namely knee flexion velocity at toe-off, knee power, and hip power (Fig. 3, Table 2). Given only three filter-based features, the percentage of correct predictions remained high (78.3% correct) using a combination of pelvic tilt at the beginning of single limb support (18.7% gait), hip flexion after the beginning of double support (52.0% gait), and peak knee flexion (79.7 ± 5.1% gait). Given only two literature-based features, the percentage of correct predictions dropped (68.1% correct) using a combination of average hip flexion moment in double support (from 47.9 ± 2.9% gait to 62.7 ± 3.5% gait) and knee flexion velocity at toe-off (62.7 ± 3.5% gait). Given only one literature-based feature, the percentage of correct predictions remained the same (67.8% correct) using knee flexion velocity at toe-off (62.7 ± 3.5% gait). Given only one filter-based feature, the percentage of correct predictions remained the same (68.2% correct) using ankle power at the beginning of double support (48.3% gait).

4. Discussion

In clinical settings, indications for rectus femoris transfer surgery generally include three features: (i) diminished range of knee flexion during swing phase, (ii) excessive rectus femoris EMG activity during pre-swing or early swing, and (iii) a positive Ely test. Several studies have suggested that statistical and regression analyses of gait data may be used to help predict outcomes of rectus femoris transfer surgeries [15–18]. Our results confirm that data mining techniques predict outcomes of rectus femoris transfer surgery in treating stiff knee gait. In evaluating subjects with stiff knee gait, linear combinations of a few significant preoperative features should be considered as additional indications for rectus femoris transfer surgery.

A combination of three preoperative gait analysis measurements correctly predicted 80% of subjects as having good outcomes

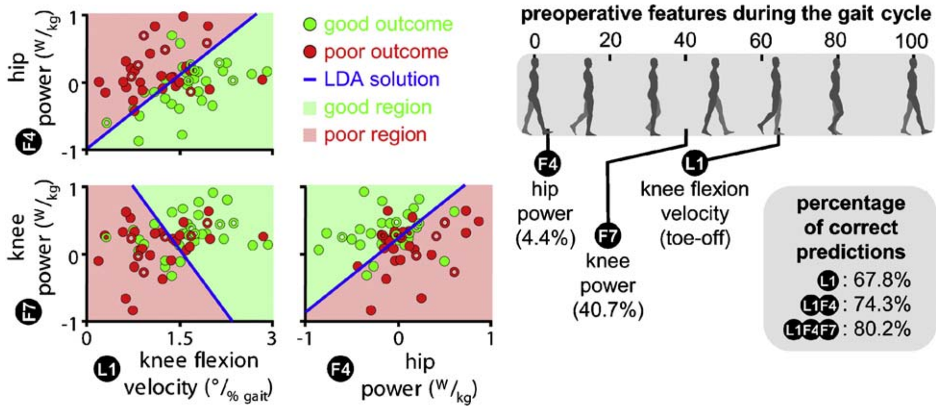

Fig. 3. Scatter plots of a combination of three significant preoperative features separating the good and poor postoperative outcome groups. Filled circles represent training data and open circles represent test data for one instance of the repeated hold-out method. Circle shading indicates good and poor postoperative outcomes. Boundary lines divide the good and poor outcome prediction regions.

Table 2
Linear discriminant analysis results for a combination of three significant preoperative features and example forms completed to predict outcomes of three subjects. Two subjects (#1 and #2) had correct outcome predictions and the third subject (#3) had an incorrect outcome prediction. The example form requires certain units for knee flexion velocity (°/% gait), hip and knee power (W/kg). Two significant figures were used for all form entries and subsequent calculations. The sum of all rows for each subject indicates the predicted outcome, where a sum less than 0.5 indicates a good outcome and more than 0.5 a poor outcome. For the subjects in this study, this combination of three significant preoperative features predicted the correct outcome in 52 of the 62 cases (84% correct).

Combination of Literature-based and Filter-based Preoperative Features	Subject #1 with Known Good Outcome		Subject #2 with Known Poor Outcome		Subject #3 with Known Good Outcome	
0.63 (regression constant)		0.63		0.63		0.63
-0.28 X knee flexion velocity at toe-off (°/% gait)	-0.28 X 1.9 =	-0.53	-0.28 X 0.63 =	-0.18	-0.28 X 0.64 =	-0.18
-0.49 X knee power at 40.7% gait (W/kg)	-0.49 X 0.42 =	-0.21	-0.49 X -0.34 =	0.17	-0.49 X -0.072 =	0.035
0.50 X hip power at 4.4% gait (W/kg)	0.50 X -0.093 =	-0.047	0.50 X 1.1 =	0.55	0.50 X 0.14 =	0.070
Outcome Prediction* (sum of all rows) *good outcome < 0.5 < poor outcome	Correctly Predicted Good Outcome	-0.16	Correctly Predicted Poor Outcome	1.2	Incorrectly Predicted Poor Outcome	0.56

following rectus femoris transfer surgery. First, the knee should have high flexion velocity (>1.2°/% gait) at toe-off. Second, the knee should be either absorbing very little power (>−0.03 W/kg), or producing mainly knee flexion power after peak knee extension in preparation for swing. Third, the hip should be either producing very little or absorbing power (<0.37 W/kg) after initial contact. More information differentiating good and poor outcome groups, including plots of these three features, is available as supplementary material online. As illustrated in Table 2 (subject #1 and #2), linearly combining these three features, already collected as a routine part of treatment planning, makes it possible to predict the outcome of rectus femoris transfer surgery for many subjects. However, there are certain subjects for whom this combination of preoperative measurements makes the incorrect outcome prediction (Table 2, subject #3).

A combination of five preoperative gait analysis measurements increases the percentage of correct predictions to roughly 88%. Two additional features in combination with the three described above are necessary. First, the hip should be highly flexed (>39°) after initial contact, in part, due to increased pelvic tilt. Second, the hip should have very low internal rotation (<20°) in early swing, in part, due to hip adduction. Linearly combining all five features makes it feasible to correctly predict outcomes for nearly nine out of 10 subjects.

There are several possible explanations why it is feasible to predict the outcome of rectus femoris transfer surgery. First, previous studies have identified preoperative features (*e.g.*, knee flexion velocity at toe-off) associated with postoperative improvements in knee flexion [18,20–22]. Second, visual inspection of mean preoperative gait analysis measures (*e.g.*, knee flexion in Fig. 1) distinguishes between good and poor outcome groups. Third, given multiple preoperative gait analysis measures with significant discriminant power, linear combinations of these measures may provide higher discriminant power than does a single measure alone.

Different combinations of significant preoperative features predicted postoperative outcomes with a high accuracy. This occurs because information within certain features (*e.g.*, joint angle, moment, and power) is not independent (*e.g.*, because joint power depends on joint moment). Also, a coefficient computed by linear discriminant analysis for a particular feature varies depending on the other features included in a feature subset. Further, adding features with nearly the same probability distributions for good and poor outcome groups may conflict with a good feature subset and suppress correct predictions by changing coefficients of the linear function of these features (*e.g.*, more than two literature-based features).

The data mining techniques used in this study have several limitations. First, the number of subjects was relatively small compared to other bioinformatics studies. However, the training set size of 50 that we fit with a linear model of three features provided an observed power of 0.99 (α = 0.05, observed R^2 = 0.34). More subjects would merely increase statistical power or perhaps allow more features to be added without a reduction of power. Second, the feature selection was based on the simplest filter-type and wrapper-type methods available; more sophisticated approaches would improve computational efficiency, allowing us to investigate larger sets of features. Third, the linear discriminant analysis was the simplest approach among the many available discriminant analysis methods; and more complex methods may improve prediction accuracy. Fourth, by carefully defining whether or not a subject walked with stiff knee gait using graded categories of four gait parameters [18], the predictive model was not contaminated by borderline cases, which allowed us to generate the best linear model to predict extremely good and poor outcomes; the percentage of correct predictions reported may change if using a different definition of stiff knee gait. Fifth, the results were generated from one database at the Center for Gait and Motion Analysis at Gillette Children's Specialty Healthcare; differing gait analysis protocols and patient populations may influence the significance of certain features and coefficients in the linear model combining these features.

Our finding that certain preoperative features are significant to predicting outcomes of rectus femoris transfer is consistent with the findings of others. Goldberg et al. [18] demonstrated the correlation between knee flexion velocity at toe-off and improvements in stiff knee gait following rectus femoris transfer surgery. Our findings support this study because knee flexion velocity at toe-off single-handedly predicted nearly 70% of outcomes. Some studies have used sagittal plane lower-body kinematics to make outcome predictions [15,16]. Our finding of significant preoperative features in both hip and knee flexion angles is consistent with these studies as well. The current work additionally demonstrates the value of joint powers in combination with three-dimensional kinematics to predict outcomes.

The potential to predict treatment outcomes for stiff knee gait is exciting and valuable. The data mining techniques in this study identified the best combinations of five or less significant features to preoperatively categorize subjects with stiff knee gait. These results indicate that a reduced set of preoperative features can distinguish between good and poor postoperative outcomes. While the intuition and experience of the clinical team are significant in recognizing indications for rectus femoris transfer, data mining provides an additional, quantitative tool for preoperative predictors of postoperative outcome. Future studies are needed to determine the ultimate set of predictors and if data mining can prospectively improve treatments.

Acknowledgements

The authors are grateful to Allison Arnold, Jennifer Hicks, Saryn Goldberg, and the staff of the Center for Gait and Motion Analysis at Gillette Children's Specialty Healthcare. This work was supported by an NSF Graduate Fellowship, NIH R01 HD046814, and NIH Roadmap for Medical Research U54 GM072970.

Conflict of interest

None of the authors had any financial or personal conflict of interest with regard to this study.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gaitpost.2009.03.008.

References

[1] Wren TAL, Rethlefsen S, Kay RM. Prevalence of specific gait abnormalities in children with cerebral palsy: influence of cerebral palsy subtype, age, and previous surgery. Journal of Pediatric Orthopaedics 2005;25:79–83.
[2] Sutherland DH, Davids JR. Common gait abnormalities of the knee in cerebral palsy. Clinical Orthopaedics 1993;288:139–47.
[3] Gage JR, Perry J, Hicks RR, Koop S, Werntz JR. Rectus femoris transfer to improve knee function of children with cerebral palsy. Developmental Medicine and Child Neurology 1987;29:159–66.
[4] Perry J. Distal rectus femoris transfer. Developmental Medicine and Child Neurology 1987;29:153–8.
[5] Asakawa DS, Blemker SS, Gold GE, Delp SL. In vivo motion of the rectus femoris muscle after tendon transfer surgery. Journal of Biomechanics 2002;35: 1029–37.
[6] Sutherland DH, Santi M, Abel MF. Treatment of stiff knee gait in cerebral palsy: a comparison by gait analysis of distal rectus femoris transfer versus proximal rectus release. Journal of Pediatric Orthopaedics 1990;10:433–41.
[7] Miller F, Dias RC, Lipton GE, Albarracin JP, Dabney KW, Castagno P. The effect of rectus EMG patterns on the outcome of rectus femoris transfers. Journal of Pediatric Orthopaedics 1997;17:603–7.

[8] Hemo Y, Aiona MD, Pierce RA, Dorociak R, Sussman MD. Comparison of rectus femoris transposition with traditional transfer for treatment of stiff knee gait in patients with cerebral palsy. Journal of Children's Orthopaedics 2007;1:37–41.
[9] Õunpuu S, Muik E, Davis RB, Gage JR, DeLuca PA. Rectus femoris surgery in children with cerebral palsy. Part II: A comparison between the effect of transfer and release of the distal rectus femoris on knee motion. Journal of Pediatric Orthopaedics 1993;13:331–5.
[10] Rethlefsen S, Tolo VT, Reynolds RA, Kay R. Outcome of hamstring lengthening and distal rectus femoris transfer surgery. Journal of Pediatric Orthopaedics 1999;8:75–9.
[11] Hadley N, Chambers C, Scarborough N, Cain T, Rossi D. Knee motion following multiple soft-tissue releases in ambulatory patients with cerebral palsy. Journal of Pediatric Orthopaedics 1992;12:324–8.
[12] Õunpuu S, Muik E, Davis RB, Gage JR, DeLuca PA. Rectus femoris surgery in children with cerebral palsy. Part I: The effect of rectus femoris transfer location on knee motion. Journal of Pediatric Orthopaedics 1993;13:325–30.
[13] Yngve DA, Scarborough N, Goode B, Haynes R. Rectus and hamstring surgery in cerebral palsy: a gait analysis study of results by functional ambulation level. Journal of Pediatric Orthopaedics 2002;22:672–6.
[14] Carney BT, Oeffinger D. Sagittal knee kinematics following combined hamstring lengthening and rectus femoris transfer. Journal of the Southern Orthopaedic Association 2003;12:149–53.
[15] Sullivan K, Miller F, Richards J, Castagno P, Lennon N. Predicting the outcome of surgery for children with cerebral palsy using pre-operative gait analysis. Gait & Posture 1995;3:92.
[16] Niiler TA, Richards JG, Miller F, Sun JQ, Castagno P. Reliability of predictions of post-operative gait in rectus transfer patients using FFT neural networks. Gait & Posture 1999;9:107.
[17] Kay RM, Rethlefsen SA, Dennis SW, Skaggs DL. Prediction of postoperative gait velocity in cerebral palsy. Journal of Pediatric Orthopaedics Part B 2001;10:275–8.
[18] Goldberg SR, Õunpuu S, Arnold AS, Gage JR, Delp SL. Kinematic and kinetic factors that correlate with improved knee flexion following treatment for stiff knee gait. Journal of Biomechanics 2006;39:689–98.
[19] Goldberg SR, Õunpuu S, Delp SL. The importance of swing-phase initial conditions in stiff knee gait. Journal of Biomechanics 2003;36:1111–6.
[20] Piazza SJ, Delp SL. The influence of muscles on knee flexion during the swing phase of gait. Journal of Biomechanics 1996;29:723–33.
[21] Kerrigan DC, Roth RS, Riley PO. The modeling of adult spastic paretic stiff-legged gait swing period based on actual kinematic data. Gait & Posture 1998;7:117–24.
[22] Riley PO, Kerrigan DC. Torque action of two-joint muscles in the swing period of stiff-legged gait: a forward dynamic model analysis. Journal of Biomechanics 1998;31:835–40.
[23] Guyon I, Elisseeff A. An introduction to variable and feature selection. Journal of Machine Learning Research 2003;3:1157–82.
[24] Liu H. Evolving feature selection. IEEE Intelligent Systems 2005;20:64–76.
[25] Fisher R. The use of multiple measurements in taxonomic problems. Annals of Eugenics 1936;7:179–88.
[26] Witten IH, Frank E. Data mining: practical machine learning tools and techniques. San Francisco: Morgan Kaufmann; 2005, 149–150.