BIOMECHANICAL SIGNAL CLASSIFICATION OF SURGICAL AND NON-SURGICAL CANDIDATES FOR KNEE ARTHROPLASTY

N. Mezghani [1,2], *M. Dunbar*[5], *Y. Ouakrim*[1,2], *A. Fuentes*[3], *A. Mitiche*[4], *S. Whynot*[6], *and G. Richardson*[5]

[1] Centre de Recherche LICEF, TELUQ university, Montreal, Canada
[2] Laboratoire LIO, Centre de Recherche du CHUM, Montreal, Canada
[3] Centre du genou EMOVI, Laval, Quebec, Canada
[4] INRS-Centre Énergie, matériaux et télécommunications, Montreal, Canada
[5] Dalhousie University, Halifax, Nova Scotia, Canada
[6] Nova Scotia Health Authority, Halifax, Nova Scotia, Canada

ABSTRACT

The purpose of this article is two-fold : (1) to select a set of biomechanical features to characterize arthroplasty candidates and, (2) design a surgical and non-surgical candidate classifier via decision trees. The biomechanical features are generated from 3D knee kinematic patterns, namely, flexion-extension, abduction-adduction, and tibial internal-external rotation measurements taken during gait recordings. The selection of features is done by incremental selection of biomechanical parametes in a classification tree of cross-sectional data. These features are then used to generate decision rules for classification. The effectiveness of the classifier is evaluated by receiver operating characteristic curve analysis, namely, the area under the curve (AUC), sensitivity, and specificity. The classification accuracy is 85% for AUC, 80% for sensitivity, and 90% for specificity. These results demonstrate the effectiveness of the selected biomechanical features and decision tree classifier to perform automatic and objective classification of surgical and non-surgical candidates for arthroplasty.

1. INTRODUCTION

Osteoarthritis (OA) of the knee, one of the most common causes of disability, continues to increase in prevalence as the older adult and obese populations grow [1]. When nonoperative treatment fails, surgical options are available to relieve pain and restore range of motion by replacing the joint articular surface with implants. The annual report of Canadian joint replacement registry indicates that in 2012-2013, there were 47,137 acute care hospitalizations for all knee replacements in Canada, representing a five-year increase of 21.5%. The economic burden of arthritis in Canada is very high and this is also true around the world. This can be attributed to several factors : the long time between the onset of symptoms and the diagnosis (estimated at about 7 years in Canada), the inadequate patient management by general practitioners with inappropriate use of costly imaging such as MRIs, unsuitable referrals to orthopedic surgeons for which patients are frequently returned to their family doctor since they are not surgical candidates (about 50%), and the increasing number of joint surgery. Thus, there is a strong need for effective management of knee OA orthopedic patients pre- and post-operatively. To determine whether an osteoarthritic patient is a candidate for joint replacement surgery, orthopedic surgeons conducts a physical examination to evaluate clinical aspects (age, signs and symptoms, range of motion, functional limitations, appropriateness for surgery, etc.). Although the radiographic severity of osteoarthritis is not always correlated with symptoms, clinicians use, generally, X-ray examination to support their decision [2]. These traditional assessments are subjective and have limited standardization which, usually, imply significant variation in surgery recommendations for patients with knee osteoarthritis (OA).

Kinematic assessment during gait, which currently can be easily acquired in clinical settings [3], provides objective and quantifiable information about knee function and offer opportunities to develop automatic objective methods of computer aided diagnosis and surgical treatement systems. Although pre-operative knee conditions, prosthesis design, and surgical techniques are generally believed to influence knee kinematics following an arthroplasty, kinematic studies have primarily focused on post-operative knee kinematics [4]. A few studies have investigated the kinematics of osteoarthritic knee pre-operatively [5, 6, 7] but none have adressed classification of surgical vs non-surgical candidates for arthroplasty using 3D kinematic data. This may be due to kinematic data complexity [8]. In particular, biomechanical data are given in the form of a vector of measurements of high dimension for each subject, causing its analysis to suffer from the curse of dimensionality. Moreover, there is a significant variability in the data. Both the variability and the high dimensionality are illustrated in Fig.1, which shows the graph of a sample of eighty-four participants curves.

The present study investigates a novel method for discriminating surgical from non surgical candidates for knee arthroplasty. The aim is to develop an automatic objective classification method to distinguish between surgical (S) and non-surgical (Non-S) candidates for arthroplasty using 3D knee kinematic signals recorded during treadmill walking episode.

2. METHODS

2.1. Database

The data was obtained from the Division of Orthopaedic Surgery in Halifax QEII Health Sciences Centre (Nova Scotia, Canada). Eighty-four participants with a primary diagnosis of moderate to severe knee OA and scheduled for arthroplasty consult, were enrolled after being seen by an orthopedic surgeon and assigned to surgical (S) or non-surgical (Non-S) groups. Table 1 summarizes the participants demographic characteristics.

	Groupe S N =44	Groupe Non-S N = 40
Age (year)	63 ± 8	64 ± 9.2
Height(m)	1.6 ± 0.4	1.6 ± 0.8
Weight (kg)	93.2 ± 25.9	89.7 ± 19.9
BMI (kg / m2)	33.2 ± 7.5	$31.2 \pm 6, 2$
Proportion of men / group	27%	44%

Table 1. Demographic characteristics and walking speed of S and Non-S groups (BMI design the mean body mass). * Student t-test revealed no significant differences between the groups ($p < 0.05$)

All participants underwent physiotherapy assessment and health surveys. Three-dimensional (3D) knee kinematics data, namely flexion-extension, abduction-adduction, and tibial internal-external rotation measurements, in the sagittal, frontal and transverse planes, respectively, were recorded while each participant walked on a treadmill at their self-selected, comfortable speed. A knee marker attachment system, the KneeKG system (EMOVI, Quebec, Canada) [3], was installed on the participant's knee to record the 3D kinematics during gait trials of 45 sec. This motion capture tool is composed of a harness and plate fixed quasi-rigidly onto the femoral condyles and tibial crest, and provides accurate, repeatable, and reliable measurements [3]. A number of representative gait cycles, generally 15, were averaged to obtain a mean pattern per subject. This was followed by interpolation and resampling from 1% to 100% of the gait cycle, therefore giving a 100 measurement points for each participant (Fig. 1).

2.2. Biomechanical feature extraction

A set of 70 biomechanical parameters was then extracted from the 3D kinematic signals. The chosen parameters were based on variables routinely assessed in clinical biomechanical studies of knee osteoarthritis populations, such as maximums, minimums, varus and valgus thrust, angles at initial contact, mean values and range of motion (ROM) throughout gait cycles or gait sub-cycles (i.e., loading, stance, swing) [9, 10]. This was followed by a feature selection step which aims at selecting a subset of the biomechanical parameters that would better discriminate between surgical and non-surgical candidates for arthroplasty.

2.3. Biomechanical feature selection and classification

Biomechanical feature selection is quite important because the number of biomechanical parameters of interest is large while the number of features that are really characteristic of surgical candidates is much smaller. We performed biomechanical feature selection using a decision tree method. More precisely, we used the classification and regression tree algorithm (CART), a scheme based on the Gini diversity index as a tree branching criterion.

Let D be a training dataset, divided into c classes $c_i, i = \{1, 2, ..., c\}$. Each subject is characterized by a vector of feature values which, in our case, correspond to the biomechanical parameters. The feature selection technique is based on the Gini gain, which is an impurity-based criterion, to select, at each internal node of the decision tree, the feature that provides the largest reduction in impurity as explained bellow.

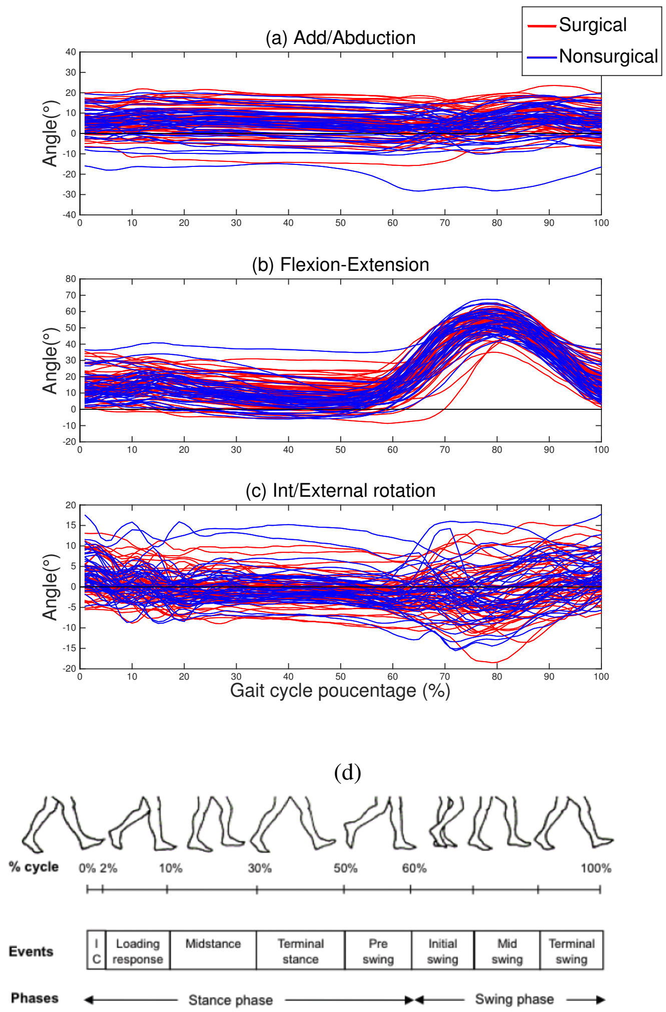

Fig. 1. Kinematic gait signals (of the database) during a gait cycle : (a) Abduction-adduction, (b) Flexion-extension, and (c) Internal-external rotation. The signals were interpolated and resampled from 1% to 100% (100 points) of the gait cycle. Each red curves represent a surgical participant and each blue one represent a Non-Surgical participant (d) The gait cycle phases.

The Gini index for the data set D is defined as :

$$Gini(D) = 1 - \sum_{i=1}^{c} p_i^2, \quad (1)$$

where p_i is the proportion of examples in D that belong to class c_i. Thus,

$$Gini(D) = 1 - \sum_{i=1}^{n} (\frac{|c_i|}{|D|})^2, \quad (2)$$

where $| \; |$ denotes the cardinal number.
Let F be a feature with m distinct values. The database D is partitioned into m subsets $\{D_1, D_2, ..., D_m\}$. The Gini index of D with respect to the feature F is defined as

$$Gini_F(D) = \sum_{i=1}^{m} \frac{|D_i|}{|D|}.Gini(D_i) \quad (3)$$

The tree branching process uses the feature F that provides the largest reduction in impurity $\Delta Gini(F)$:

$$\Delta Gini(F) = Gini(D) - Gini_F(D) \tag{4}$$

Once the biomechanical feature selection is performed, a decision tree is built using the selected feature and used for classification.

2.4. Performance evaluation

We used the ROC (Receiver Operating Characteristics) curve to select biomechanical parameters. The ROC curve is a graphic representation of the relationship between sensitivity and specificity which is used to select the fetaure that better discriminates between surgical and non-surgical candidates.

The classifier performance was evaluated using sensitivity (Se), specificity (Sp) and accuracy rate (τ) :

$$Se = \frac{TP}{TP + FN}$$

$$Sp = \frac{TN}{TN + FP}$$

$$\tau = \frac{TP + TN}{TP + TN + FP + FN},$$

where TP is the number of true positives, i.e., the number of surgical participants correctly classified as surgical candidates and TN is the number of true negatives. FP is the number of false positives, i.e., the number of non-surgical participants correctly classified as non surgical candidates, and FN is the number of false negatives.

The classifications results were evaluated by leave-one-out cross validation, which is a common procedure in classification evaluation. It consist on extracting one sample for validation, the rest of the samples of the data set being used for learning. This procedure is repeated N times, with N, the number of samples in the dataset. The performance is computed over all examples in the sample.

2.5. Statistical analysis

We performed a $t-$test statistical analysis to examine the general participant characteristic differences between the two groups. The statistical analysis was conducted using SPSS 20.0 (Statistical Package for Social Sciences). A P-value of 0.05 was set as the level of statistical significance.

3. RESULTS

Among the 70 biomechanical parameters of interest extracted, a set of 3 parameters was selected to characterize surgical and non-surgical candidates : The minimum of the flexion/extension angle curve, the rotation angle at the push off phase (54%) and the rotation angle at mid stance phase (35%) of the gait cycle. Figure 2 shows the resulting decision tree with the corresponding the threshold values.

An ROC curve of Fig. 3 shows the relationship between sensitivity and specificity. The AUC reaches 0,8477

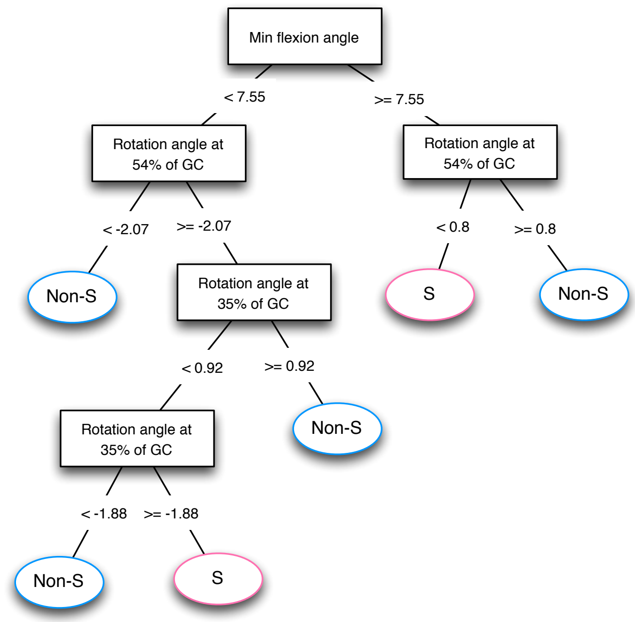

Fig. 2. The obtained decision tree.

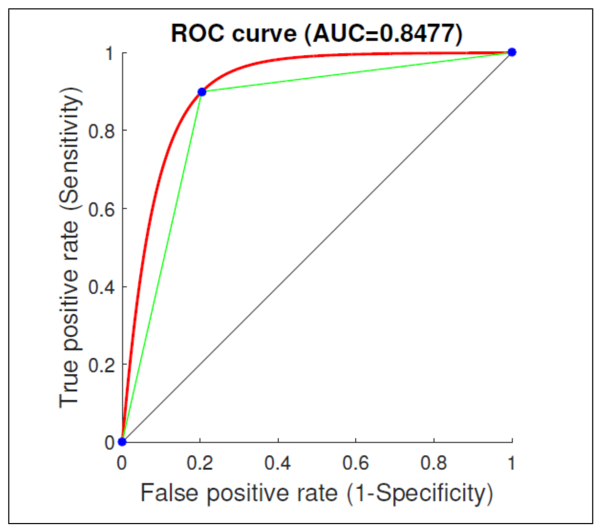

Fig. 3. The ROC curve.

The confusion matrix in Table 2 summarizes the performance of the decision tree classifier (Figure 2). Each column of the matrix represents the instances in a predicted class, while each row represents the instances in the actual class, i.e., as assigned by the arthroplasty surgeon diagnosis. The classifier performance was 84.7% for the classification accuracy, 79.5% for sensitivity, 90% for specificity.

The statistical analysis of the participants demographic characteristics (Table 1), confirms that there is no statistically significant difference between the general participant characteristic of the two groups. Therefore, the distinction is due to the participants knee kinematic data, not to subject characteristics.

		Predicted class	
		S	Non-S
Real class	S	35	9
	non-S	4	36

Table 2. Confusion matrix

4. CONCLUSION

In this study, we developed a biomechanical data classifier to distinguish between surgical and non-surgical candidates for arthroplasty. The results show strong correlations between expert clinical assessment and kinematic objective evaluation, to distinguish between S from Non-S candidates. In future studies, we will add objective data sets (Oxford Knee Score, BMI) as inputs in the decision tree to improve classification performance.

The development of a clinically validated, objective assessment method to discriminate surgical and non-surgical candidates for arthroplasty will allow better triage of knee OA patients and streamline use of hospital resources, and provide better rationalization of services to significantly improve patient care.

5. REFERENCES

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