Gait & Posture 52 (2017) 45–51

Contents lists available at ScienceDirect

Gait & Posture

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

Full length article

Predicting postoperative gait in cerebral palsy

Omar A. Galarraga C.[a,b], Vincent Vigneron[b], Bernadette Dorizzi[c], Néjib Khouri[a,d], Eric Desailly[a,*]

[a] UNAM, Pôle Recherche & Innovation, Fondation Ellen Poidatz, 1 Rue Ellen Poidatz, Saint-Fargeau-Ponthierry, France
[b] IBISC—EA 4526, Université d'Evry Val d'Essonne, 40 Rue du Pelvoux, Courcouronnes, France
[c] SAMOVAR—UMR 5157, Télécom SudParis, Institut Mines-Télécom, 9 Rue Charles Fourier, Evry, France
[d] Chirurgie Orthopédique Pédiatrique, Hôpital Universitaire Necker-Enfants Malades, 149 Rue de Sèvres, Paris, France

ARTICLE INFO

Article history:
Received 13 January 2016
Received in revised form 6 September 2016
Accepted 6 November 2016

Keywords:
Cerebral palsy
Single-event multilevel surgery
Outcome prediction
Clinical gait analysis
Machine learning

ABSTRACT

In this work, postoperative lower limb kinematics are predicted with respect to preoperative kinematics, physical examination and surgery data. Data of 115 children with cerebral palsy that have undergone single-event multilevel surgery were considered. Preoperative data dimension was reduced utilizing principal component analysis. Then, multiple linear regressions with 80% confidence intervals were performed between postoperative kinematics and bilateral preoperative kinematics, 36 physical examination variables and combinations of 9 different surgical procedures. The mean prediction errors on test vary from 4° (pelvic obliquity and hip adduction) to 10° (hip rotation and foot progression), depending on the kinematic angle. The unilateral mean sizes of the confidence intervals vary from 5° to 15°. Frontal plane angles are predicted with the lowest errors, however the same performance is achieved when considering the postoperative average signals. Sagittal plane angles are better predicted than transverse plane angles, with statistical differences with respect to the average postoperative kinematics for both plane's angles except for ankle dorsiflexion. The mean prediction errors are smaller than the variability of gait parameters in cerebral palsy. The performance of the system is independent of the preoperative state severity of the patient. Even if the system is not yet accurate enough to define a surgery plan, it shows an unbiased estimation of the most likely outcome, which can be useful for both the clinician and the patient. More patients' data are necessary for improving the precision of the model in order to predict the kinematic outcome of a large number of possible surgeries and gait patterns.

1. Introduction

Orthopaedic surgery is usually performed in order to lessen gait abnormalities observed in patients with cerebral palsy (CP). Multiple bones and muscles are operated during a Single Event Multilevel Surgery (SEMLS) [1], which combines several procedures in the same surgery.

Clinical Gait Analysis (CGA) is used in combination with physical examination in order to propose a suitable surgery to patients with CP [1]. However, surgical decision making is not yet fully standardized. Different surgical procedures may be proposed to address the same gait deviation and different decision making algorithms may be used by medical teams to define surgical plans. Moreover, once the indication is established it is difficult for the surgeon and furthermore for the patient to predict the effect of the surgery. Recently, several decision-making tools based on statistical machine learning have been developed for predicting surgery outcome in SEMLS. Reinbolt et al. [2] used linear discriminant analysis for predicting good or bad outcomes of rectus femoris transfer for patients with stiff knee. For predicting good or bad outcomes of hamstring lengthening, Arnold et al. [3] utilized hierarchical log-linear analysis and Sebsadji et al. [4] used support vector machines both combined with musculoskeletal models. Schwartz et al. [5] used random forests for predicting good or bad outcomes of psoas lengthening. All of the above methods give qualitative outcome predictions of improvement or non-improvement, but they do not help the surgeon nor the patient to predict how the latter will walk after surgery.

Some other methods predict some quantitative gait parameters. Hicks et al. [6] used multiple linear regression for predicting post-treatment knee flexion during stance for patients presenting crouch gait and also established good or bad outcomes based on these predictions. Sullivan et al. [7] used regression analysis and

* Corresponding author at: 1 Rue Ellen Poidatz, 77310 Saint Fargeau-Ponthierry, France.
E-mail address: eric.desailly@fondationpoidatz.com (E. Desailly).

http://dx.doi.org/10.1016/j.gaitpost.2016.11.012
0966-6362/

Hersh et al. [8] used artificial neural networks to predict knee flexion during gait after rectus femoris transfer. Galarraga et al. [9] utilized artificial neural networks for predicting postoperative knee flexion and pelvic tilt at initial contact with or without hamstring lengthening. All previous works already mentioned are based on one type of abnormal gait patterns in CP (i.e. stiff knee or crouch gait) or on one principal surgical procedure, without considering the effect of other surgical procedures and their combinations. Niiler et al. [10] considered rectus femoris transfer and concurrent surgeries (hamstring lengthening, Achilles lengthening and gastrocnemius lengthening) of 68-patient series (94 lower limbs) and performed linear regressions for predicting postoperative knee range of motion during gait.

Despite these previous works, surgery planning remains difficult and global gait outcome prediction is still incomplete. Moreover, it is difficult to explain postoperative expected outcome to patients and their families, who might struggle to imagine a realistic outcome based on the predicted parameters.

The objective of this study was to use statistical machine learning techniques to develop a system able to predict postoperative kinematic curves of children with CP based on preoperative physical examination and 3-D gait analysis, and a proposed surgery plan.

2. Materials and methods

2.1. Population and data description

This retrospective study analyzed anonymous data of children with CP that have undergone SEMLS within a ten year period between 2004 and 2014. These children have had physical examination and CGA before and at least one year after surgery. Gait analysis was performed pre and postoperatively in the same laboratory. From 2004 to 2007, the acquisition was performed with a SAGA 3RT Biogesta system and, since 2008, with a Vicon system. Lower limb marker placements were identical in all the exams and kinematic data were computed from the acquisition's raw data (marker coordinates) with the same custom software based on a modified Helen Hayes [11,12] model with anatomical markers on the femoral condyles and the medial-malleolus. Fifteen kinematic angles were considered for each patient: pelvic tilt, pelvic obliquity, pelvic rotation and hip flexion, hip adduction, hip rotation, knee flexion, ankle dorsiflexion and foot progression for both lower limbs. Surgical data were decomposed into combinations of $N_s = 9$ surgery categories: hip bony surgery, hip soft tissue surgery, rectus femoris surgery (transfer or release), hamstring lengthening, patella lowering, distal femoral osteotomy, shank bony surgery, ankle-foot soft tissue surgery and foot bony surgery. The surgical categories have been established depending on their functional objective and joint or segment that is modified. In these categories, some different surgical procedures are grouped in the same class if their functional objective and the affected joints or segments are alike [see Supplementary data for examples]. For each lower limb j, a surgery binary code $S_j = \begin{pmatrix} s_{j,1} & \cdots & s_{j,N_s} \end{pmatrix}^T$ was attributed where $s_{j,i} = \begin{cases} 1 \text{ if gesture } i \text{ was conducted on patient } j \\ 0 \text{ if gesture } i \text{ was not conducted on patient } j \end{cases}$ with $i = 1, \ldots, N_s$ and T is the transpose operator.

2.2. Preprocessing

The variables that have been measured during physical examination varied depending on the patient and the clinician that performed the exam. For this reason, we considered 36 parameters that were measured at a minimum rate of 80% in our database. These parameters include information about size and weight; hip, knee and ankle ranges of motion; muscle force; and spasticity (details in Supplementary data).

Fig. 1 shows all the stages of the method. Physical examination missing data were replaced using iterative robust model-based imputation (IRMI) [13]. This technique consists on initializing missing values and then iteratively perform linear regressions of each column with respect to the others. The initialization begins by searching the lower limbs with the nearest physical examination profile considering only the non-missing data with a k-Nearest Neighbor algorithm [14] for $k = 5$ and ends by replacing each missing value by the median over the 5 nearest neighbors.

Kinematic data were automatically segmented into gait cycles utilizing the high pass algorithm (HPA) [15]. Then gait cycles were resampled and normalized to 51 points (2% of gait cycle) as in [16] and mean gait cycles were computed for each limb. A right and a left kinematic preoperative gait vectors were composed with the fifteen kinematic signals of both limbs normalized respectively by

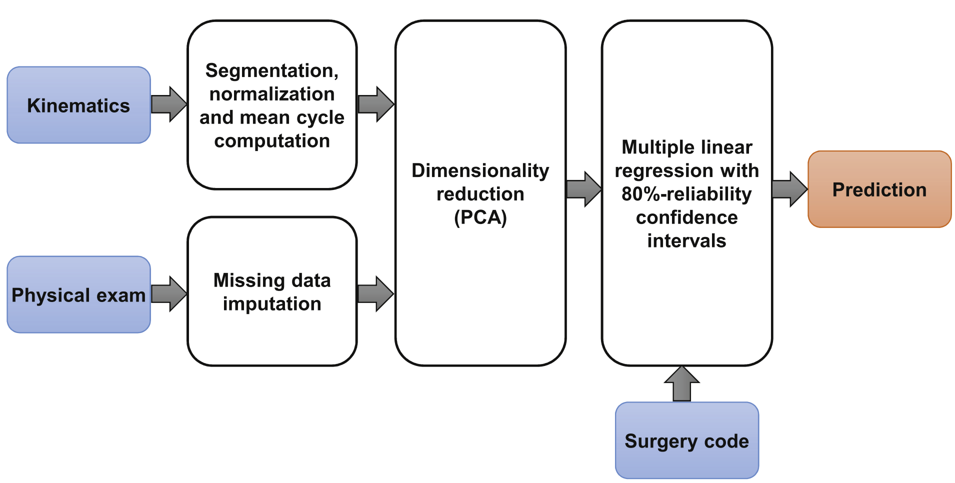

Fig. 1. Method stages from CGA and physical examination data (see Supplementary data) to prediction. Kinematic signals were segmented into gait cycles and normalized to 51 points per angle and cycle. Missing data from physical examination were imputed with the IRMI algorithm. The dimension of the concatenated vectors of preprocessed kinematics and physical examination data (see Supplementary data) was reduced using PCA. Then a multiple linear regression between postoperative kinematics and the low-dimensional preoperative vectors and surgery codes was performed. Confidence intervals with 80% reliability were computed.