Estimation of Postoperative Knee Flexion at Initial Contact of Cerebral Palsy Children using Neural Networks

Omar A. Galarraga C.[1,2], Vincent Vigneron[2], Bernadette Dorizzi[3], Néjib Khouri[1,4] and Eric Desailly[1]

[1]*UNAM, Pôle Recherche & Innovation, Fondation Ellen Poidatz, 1 rue Ellen Poidatz, Saint-Fargeau-Ponthierry, France*

[2]*IBISC EA 4526, Université d'Evry Val d'Essonne, 40 rue du Pelvoux, Courcouronnes, France*

[3]*Institut Mines-Télécom, Télécom SudParis, UMR 5157 SAMOVAR, 9 rue Charles Fourier, Evry, France*

[4]*Hôpital Universitaire Necker-Enfants malades, 149 rue de Sèvres, Paris, France*

Keywords: Clinical Gait Analysis, Nonlinear Data Fitting, Neural Networks, Cerebral Palsy, Biomechanics.

Abstract: Cerebral Palsy (CP) affects walking and often produces excessive knee flexion at initial contact (KFIC). Hamstring lengthening surgery (HL) is applied to decrease KFIC. The objective of this work is to design a simulator of the effect of HL on KFIC that could be used as a decision-making tool. The postoperative KFIC is estimated given the preoperative gait, physical examination and the type of surgery. Nonlinear data fitting is performed by feedforward neural networks. The mean regression error on test is 9.25° and 63.21% of subjects are estimated within an error range of 10°. The simulator is able to give good estimations independently of the preoperative gait parameters and the type of surgery. This system predicts the outcomes of orthopaedic surgery on CP children with real gait parameters, and not with qualitative characteristics.

1 INTRODUCTION

Cerebral Palsy (CP) is an umbrella term that refers to a group of neurological disorders from brain damage that affect human movement, balance and posture. These disorders frequently entail muscle and bone deformities. Two typical CP gait troubles are crouch gait and equinus gait (Gage et al., 2009): crouch gait is principally characterized by excessive knee flexion during walking, while equinus gait refers to ground contact first done by the toes instead of the heel.

In order to lessen these pathological gait patterns, orthopaedic surgery is usually performed on CP patients. Multiple bone and soft tissue deformities can be corrected during a single-event multilevel surgery (SEMLS) which combines several surgical gestures according to the functional objective, the technique applied, the body parts that are affected, etc. For instance, the most common treatment for crouch gait is hamstring lengthening. Its purpose is to decrease knee flexion at ground contact by increasing hamstrings length surgically. This surgery has reportedly given good results (Ma et al., 2006), however its indication is not always straightforward. First because this surgery may have side effects on pelvic tilt. Second because at this time there is currently no method or simulation tool, other than the surgeon experience, that is able to predict hamstring lengthening effect on knee flexion at initial contact. Physical examination and clinical gait analysis (CGA) (Gage et al., 2009) are performed on patients to improve diagnosis and assert suitable treatments. Specifically for the first point, most of the useful results are related to musculoskeletal simulations (Arnold et al., 2006; Desailly, 2008; Sebsadji et al., 2012).

On the other hand, simulation studies for predicting effect of treatment on CP gait are rare, *e.g.* on equinus gait (Armand et al., 2007) or on effect of rectus femoris transfer surgery (Reinbolt et al., 2009). In both studies, the estimations are *qualitative*, *i.e.* they can only predict "good" or "bad" outcomes, but not values of gait parameters. In addition, there is no reported study about simulation of the effects of hamstring lengthening on CP gait.

In this paper the effect of SEMLS on gait is evaluated, in particular the effect of hamstring lengthening on knee gait flexion at initial contact. Initial contact is the stage of gait cycle when foot strikes the floor, as

Galarraga C. O., Vigneron V., Dorizzi B., Khouri N. and Desailly E..
Estimation of Postoperative Knee Flexion at Initial Contact of Cerebral Palsy Children using Neural Networks.
DOI: 10.5220/0005286503380342
In *Proceedings of the International Conference on Pattern Recognition Applications and Methods* (ICPRAM-2015), pages 338-342
ISBN: 978-989-758-077-2

can be seen in figure 1.

The objective of this work is to design a simulator that could be applied as a decision-making tool for including or not the hamstring lengthening procedure in a SEMLS context.

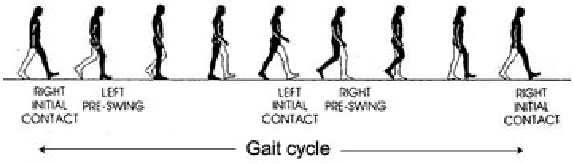


Figure 1: Gait cycle stages (gai, 2014).

To achieve the objective, supervised learning techniques are applied on data of CP children that underwent SEMLS (section 3). Post-surgical knee flexion at initial contact is estimated knowing pre-surgical gait and physical examination, given a surgery. The nonlinear regression is performed by multi-layer feedforward neural networks.

2 DATA DESCRIPTION

All the patients in the database have undergone surgery and have had at least a CGA before and after the surgery. To simplify the problem, both sides lower limbs are considered independently. In total there are $N = 193$ limbs corresponding to $N_{pat} = 100$ patients (7 limbs are not valid due to lack of information whether on CGA or the physical exam). Male subjects represent 61% of the population and 39% are female. The mean ages and standard deviation of the patients at the three different stages considered (Preoperative CGA, surgery and Postoperative CGA) can be seen in table 1.

Table 1: Distribution of patients ages at CGAs and surgery.

	μ	σ
Preoperative CGA	11.80	3.30
Surgery	12.60	3.24
Postoperative CGA	14.76	3.32

For each CGA, we consider fifteen gait angles at initial contact, as shown in figure 2. The mean of each of these angles is computed when several gait cycles are available (multiple initial contacts). Physical examinations provide preoperative *popliteal* angles (PoplA).

We collect $n = 714$ walk cycles ($n \gg 193$ because we record several walk cycles per patient) and denote our observation set by $(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_n, y_n)$ that may be regarded as a finite realization of a multivariate

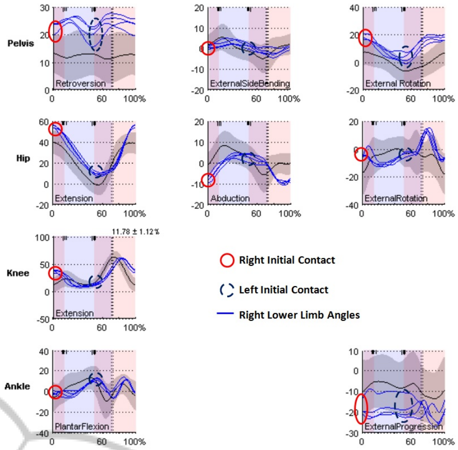


Figure 2: Considered gait angles. Example for the right lower limb signals. The left lower limbs signals are also considered at both sides initial contacts.

stochastic data collection. The parameters used for the computation are defined as:

PTIC	Pelvis Tilt
POIC	Pelvis Obliquity
PRIC	Pelvis Rotation
HFIC	Hip Flexion
HAIC	Hip Abduction
HRIC	Hip Rotation
KFIC	Knee Flexion
AFIC	Ankle DorsiFlexion
FFIC	Foot-Ground Flexion
$\mathrm{HF}_{cont}\mathrm{IC}$	Contralateral Hip Flexion
$\mathrm{HA}_{cont}\mathrm{IC}$	Contralateral Hip Abduction
$\mathrm{HR}_{cont}\mathrm{IC}$	Contralateral Hip Rotation
$\mathrm{KF}_{cont}\mathrm{IC}$	Contralateral Knee Flexion
$\mathrm{AF}_{cont}\mathrm{IC}$	Contralateral Ankle Flexion
$\mathrm{FF}_{cont}\mathrm{IC}$	Contralateral Foot Flexion

The above angles are in degrees and are measured at initial contact (see figure 1).

3 METHOD

First, input variables are selected from all available data. Second, a nonlinear regression of the post-surgical knee flexion angle during gait is done by a feedforward neural network. Leave-one-out cross-validation (Bishop, 2006) is performed in order to have a measure of the regression error for each patient in the database.

The variable selection is done by a ranking technique adding a prone variable (Guyon and Elisseeff, 2003). The variables ranked higher than the prone are selected as inputs for the neural network. Variables ranked lower than the prone are rejected as entries.

The prone is a completely random variable unrelated to the target output.

The ranking technique consists on a Gram-Schmidt orthogonalization (Dreyfus et al., 2008; Guyon and Elisseeff, 2003). If $P_1, \ldots, P_k$ are the k vectors corresponding to the candidate variables, R is the prone and Y is the target output vector, this iterative procedure is described by algorithm 1, where $\langle\langle A, B\rangle\rangle$ is the inner product of vectors A and B.

Algorithm 1: Gram-Schmidt variable ranking with prone.

$P_{k+1} \leftarrow R$
for $i = 1$ **to** $k+1$ **do**
  $Z_i \leftarrow \underset{P_j, j=1,\ldots,k+1}{\arg\max} \frac{\mathrm{Cov}(P_j, Y)}{\sigma_{P_j}\sigma_Y}$
  for $j = 1$ **to** $k+1$ **do**
    $P_j \leftarrow P_j - \frac{\langle\langle P_j, Z_i\rangle\rangle}{\langle\langle Z_i, Z_i\rangle\rangle} Z_i$
  end for
  $Y \leftarrow Y - \frac{\langle\langle Y, Z_i\rangle\rangle}{\langle\langle Z_i, Z_i\rangle\rangle} Z_i$
end for

At the first iteration in algorithm 1, the candidate variable that is most correlated with the target output is selected. Then all the candidate variables and the target output are projected into the orthogonal space of the selected variable. In this new space, again the variable which is the most correlated to the target is chosen. This process is repeated until all variables are ranked.

The candidate variables are the fifteen preoperative mean gait angles at foot strike and the preoperative popliteal angle.

The selected variables are the input of the neural network plus a binary input corresponding to the inclusion of hamstrings lengthening surgery. $HL = 1$ means that the hamstrings lengthening was performed and $HL = 0$ means that another kind of surgery was applied. The target output is the postoperative knee flexion angle at initial contact (KFIC$_{post}$).

The neural network architecture consists of a multi-layer perceptron with one hidden layer. The number of hidden units is optimized using the validation error rates. The learning method is the Levenberg-Marquardt algorithm (Bishop, 2006). Preprocessing consists on centering and normalizing data.

In order to have a measure of the error for all the patients in the database, a neural network is trained for each subject, then tested only for the subject in question. For each neural network, the training set is composed of all the available gait cycles, except for those belonging to the patient that will be tested. Test is performed only over the mean cycle angles per patient. The architecture of the neural networks is always identical.

The leave-one-out cross-validation (Duda et al., 2001) is performed $M = 10$ and then the mean errors per patients are calculated, as shown in algorithm 2. The error measure considered for each patient i is the root mean-square error (RMSE) computed as in equation 1.

Algorithm 2: Leave-one-out cross-validation.

for $i = 1$ **to** M **do**
  for $j = 1$ **to** N_{pat} **do**
    Initialize NN
    Train NN without patient j
    Test patient j
  end for
end for
Compute mean errors

$$RMSE^i = \sqrt{(Y_i - g(X_i))^2} = |Y_i - g(X_i)| \quad (1)$$

4 RESULTS

From the list of variables in section 2, the selected inputs ordered by relevance are: KFIC, FF$_{cont}$IC, PoplA, HR$_{cont}$IC, AFIC, HA$_{cont}$IC and PTIC.

Best results were obtained for $m = 10$ hidden units. Figure 3 shows the estimated KFIC with respect to the real KFIC$_{post}$ for one of the multiple leave-one-out procedures (see section 3). The black line corresponds to the ideal estimation and points between the two red lines stay within a 10° RMSE range.

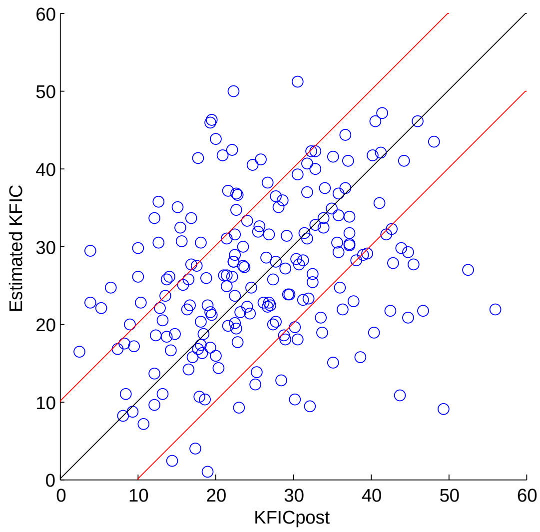


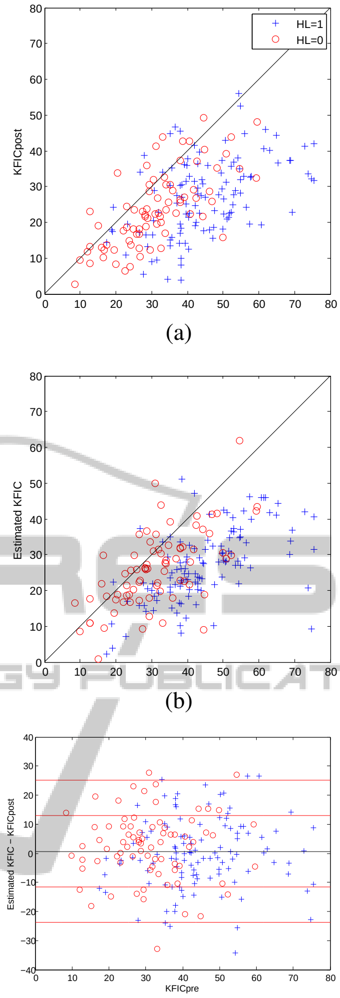
Figure 3: Estimated vs. real post-surgical knee flexion.

Table 2: Test results per patient and given the type of surgery.

		RMSE	
Subjects	$\mu_{RMSE} \pm \sigma_{RMSE}$	$\leq 10^\circ$	$\leq 15^\circ$
All	$9.25^\circ \pm 5.45^\circ$	63.21%	86.53%
$HL = 1$	$9.36^\circ \pm 5.68^\circ$	62.61%	85.22%
$HL = 0$	$9.09^\circ \pm 5.13^\circ$	64.10%	88.46%

In table 2, mean RMSE and the corresponding standard deviations can be observed for all patients, those who underwent hamstring lengthening ($HL = 1$) and those who had another type of surgery. In addition, percentages of subjects within 10° and 15° RMSE range are also given.

To show the relation between the outputs (target, estimated and errors), figure 4 shows these three outputs with respect to the preoperative knee flexion at initial contact. In 4(a) and 4(b), points over the black line correspond to patients where the KFIC increased. On the other hand, in figure 4(c), the black line represents the mean of the difference between estimated KFIC and KFIC$_{post}$. The red lines correspond to plus and minus one and two standard deviation respectively. In all the images previous mentioned, blue crosses represent subjects that underwent hamstring lengthening and red circles correspond to subjects that had another kind of surgery.



(c)

Figure 4: Target, estimation and error with respect KFIC$_{pre}$. (a) KFIC$_{post}$ vs. KFIC$_{pre}$. (b) Estimated KFIC vs. KFIC$_{pre}$. (c) Difference between estimated KFIC and KFIC$_{post}$ vs. KFIC$_{pre}$.

5 DISCUSSION

The variable selection applied allows to decrease the dimension of the problem from 16 to 7, which is less than the half. This also decreases complexity of the nonlinear regression. Moreover, with the Gram-Schmidt orthogonolization, we maximize the correlation of the input with the target output and, at the same time, we reduce redundancy between the entry variables.

Since surgical treatment implies various risks and potential complications, a threshold for the difference between estimated and measured postoperative knee flexion has to be defined in order to determine wether or not an estimation is acceptable. If we consider that intrasubject gait variability is higher in CP children than in normal children (Steinwender et al., 2000), that the interlaboratory gait variabilty for knee flexion is 13° in (Noonan et al., 2003) and that there are uncertainties associated to CGA (Charlton et al., 2004; Groen et al., 2012) and surgery, we define as acceptable an estimation with maximum 10° of error. The system estimates 63.21% of patients within this error range (see table 2). The error rates are almost the same for both groups of patients: those who underwent hamstring lengthening and those who had another surgery.

On the other hand, the distribution of points in figures 4(a) and 4(c) are similar, and they have the same proportion of data above and below the black line. This means that the system can forecast bad (above the black line) and good outcomes. In figure 4(c), we can observe that the systems overestimates and underestimates uniformly with respect to preoperative knee flexion at initial contact. Additionally, errors are equally distributed in function of the KFIC$_{pre}$ input independently if the subjects had or not hamstring lengthening.

6 CONCLUSIONS

The proposed simulator can estimate the postoperative knee flexion at initial contact, given the preoperative gait, physical examination and a surgery. On test, 63.21% of the $N = 193$ limbs are estimated with an acceptable regression error (see section 5). In addition, the mean RMSE is 9.25°, which means that the expected error of regression is also acceptable (inferior to 10°).

The developed system is able to give good estimations independently of the preoperative gait parameters and the type of surgery. However, around a third of the patients are not well estimated. For the application, it is important to apply surgery only if a good result can be asserted. Conversely, it is crucial to avoid a surgery plan if a bad outcome is most likely. For this reason, it would be interesting to detect *a priori* patients that will be badly estimated. With this strategy, patients more likely to be badly estimated, could be rejected by the simulator. For example, if a new patient is too far from the training patients in the input space, no estimation will be given.

In order to improve estimation, a prior clustering of the patients could be applied, so the regression method would be able to adapt to the *type* of subject.

Finally, this study predicts the outcomes of orthopaedic surgery with real gait parameters, and not with qualitative parameters that are too relative and ambiguous for such a sensitive application.

Further work will focus on estimating the whole postoperative knee flexion gait cycle signal and not only the initial contact point.

ACKNOWLEDGEMENTS

This work is part of a project funded by the Fondation Ellen Poidatz, the Fondation Bettencourt Schueller and the Region Ile de France. The authors would like to thank the UNAM medical and technical team of the Fondation Ellen Poidatz, who recorded all data used in this work.

REFERENCES

Walking in graphs. http://www.utdallas.edu. Accessed: 2014-10-09.

Armand, S., Watelain, E., Roux, E., Mercier, M., and Lepoutre, F.-X. (2007). Linking clinical measurements and kinematic gait patterns of toe-walking using fuzzy decision trees. *Gait & Posture*, 25(3):475–484.

Arnold, A. S., Liu, M. Q., Schwartz, M. H., Õunpuu, S., and Delp, S. L. (2006). The role of estimating muscle-tendon lengths and velocities of the hamstrings in the evaluation and treatment of crouch gait. *Gait & Posture*, 23(3):273–281.

Bishop, C. (2006). *Pattern Recognition and Machine Learning*. Information Science and Statistics. Springer.

Charlton, I., Tate, P., Smyth, P., and Roren, L. (2004). Repeatability of an optimised lower body model. *Gait & Posture*, 20(2):213–221.

Desailly, E. (2008). *Analyse biomécanique 3D de la marche de l'enfant déficient moteur. Modélisation segmentaire et modélisation musculo-squelettique*. PhD thesis, Université de Poitiers.

Dreyfus, G., Martinez, J.-M., Samuelides, M., Gordon, M., Badran, F., and Thiria, S. (2008). *Apprentissage statistique*. Eyrolles, Paris, 3rd edition.

Duda, R., Hart, P., and Stork, D. (2001). *Pattern Classification*. Wiley-Interscience, 2nd edition.

Gage, J., Schwartz, M., Koop, S., and Novacheck, T., editors (2009). *The Identification and Treatment of Gait Problems in Cerebral Palsy*. Mac Keith Press, 2nd edition.

Groen, B., Geurts, M., Nienhuis, B., and Duysens, J. (2012). Sensitivity of the OLGA and VCM models to erroneous marker placement: Effects on 3d-gait kinematics. *Gait & Posture*, 35(3):517–521.

Guyon, I. and Elisseeff, A. (2003). An introduction to variable and feature selection. *The Journal of Machine Learning Research*, 3:1157–1182.

Ma, F. Y. P., Selber, P., Nattrass, G. R., Harvey, A. R., Wolfe, R., and Graham, H. K. (2006). Lengthening and transfer of hamstrings for a flexion deformity of the knee in children with bilateral cerebral palsy TECHNIQUE AND PRELIMINARY RESULTS. *Journal of Bone & Joint Surgery, British Volume*, 88(2):248–254.

Noonan, K. J., Halliday, S., Browne, R., O'Brien, S., Kayes, K., and Feinberg, J. (2003). Interobserver variability of gait analysis in patients with cerebral palsy. *Journal of Pediatric Orthopaedics*, 23(3):279–287.

Reinbolt, J. A., Fox, M. D., Schwartz, M. H., and Delp, S. L. (2009). Predicting outcomes of rectus femoris transfer surgery. *Gait & Posture*, 30(1):100–105.

Sebsadji, A., Khouri, N., Djemal, K., Yepremian, D., Hareb, F., Hoppenot, P., and Desailly, E. (2012). Description and classification of the effect of hamstrings lengthening in cerebral palsy children multi-site surgery. *Computer Methods in Biomechanics and Biomedical Engineering*, 15(sup1):177–179.

Steinwender, G., Saraph, V., Scheiber, S., Zwick, E. B., Uitz, C., and Hackl, K. (2000). Intrasubject repeatability of gait analysis data in normal and spastic children. *Clinical Biomechanics*, 15(2):134–139.