# A Predictive Rehabilitation Software for Cerebral Palsy Patients

J. Bouchard, B. Prosperi, G. Bavre, M. Daudé, and E. Jeandupeux

***Abstract*****—**Young patients suffering from Cerebral Palsy are facing difficult choices concerning heavy surgeries. Diagnosis settled by surgeons can be complex and on the other hand decision for patient about getting or not such a surgery involves important reflection effort. Proposed software combining prediction for surgeries and post surgery kinematic values, and from 3D model representing the patient is an innovative tool helpful for both patients and medicine professionals. Beginning with analysis and classification of kinematics values from Data Base extracted from gait analysis in 3 separated clusters, it is possible to determine close similarity between patients. Prediction surgery best adapted to improve a patient gait is then determined by operating a suitable preconditioned neural network. Finally, patient 3D modeling based on kinematic values analysis, is animated thanks to post surgery kinematic vectors characterizing the closest patient selected from patients clustering.

***Keywords*****—**Cerebral Palsy, Clustering, Crouch Gait, 3-D Modeling.

## I. Introduction

CEREBRAL PALSY (CP) is a disease often appearing on premature baby, and causes cognitive, sensory and motor disability which occurs during brain development at fetus stage. This is a non-progressive disease affecting the movements of the person. The present study is focusing on CP motor aspect by investigating how people suffering from this disease are affected in their walk with consequent crouch gait [1], [2], [14], [15], [16], [17], [18]. The multiple biomechanical origins such as spasticity, ataxy or athetosis which induce bone deformations and stiffness in the lower limbs [6], [7] are the many parameters to take into account in order to clearly identify the sources of patient erroneous walk [1], [2], [9]. After identifying the causes of crouch gait, the most adapted treatments can be applied and are composed of long recovery ones such as heavy surgeries [5], and/or more simple ones such as physiotherapy for those willing to avoid a 2 year recovery. Patients suffering from this disease are often diagnosed by using the clinical gait analysis which permits to collect qualitative data on patient walk using goniometers, pressure sensors on the floor and electro-myographers [1], [6], [9], [14]. A database gathering together kinematic data on patients before and after treatment [10], treatments applied on them and basic data such as age and weight, has been used. Project first objective is to facilitate the diagnostic of biomechanical causes on the walk [3] in order to help identifying the right treatment using only kinematic data collected from clinical gait analysis [5], [7], [14], [18]. Second objective is to help the patient to identify himself through a surgical effect simulator allowing him to preview his walk after treatment.

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In order to do the task the project has been split in 3 main parts. In first part the collected patient data have been clustered using an offline algorithm called “K-means” in a database in order to separate them in 3 groups of similar kinematic parameters. In second part an online neural network algorithm has been applied to identify the best treatment for a patient using previously collected patient database.

The last part is the personalized avatar walk simulator displaying visually patient expected walk after treatment using physical and kinematic parameters. To complete successfully the project, common software programs such as Matlab, Octave, Blender and MakeHuman have been used.

## II. Clustering

The database extraction step is a fundamental milestone. The goal is to understand what information is crucial to next step clustering work. Kinematic data (gait vector) and combinations of surgery presented in binary way are finally the only data used in the work [13]. With Matlab software, a selection of well documented data specific to 40 patients has been collected in the database and automatically performed. Thus the final database consists of 80 limbs (40×2) with gait vectors of left and right legs. These vectors represent angles of 9 hinge axis. Angle values are those defining gait movements of pelvis (ante retroversion, inclination, rotation), hip (flexion/extension, abduction/induction, transverse rotation), knee (flexion/extension), ankle (flexion/extension) and foot (rotation) [5], [7], [8], [10], [13], [14].

Knowing that each articulation is composed of 51 values through a gait cycle, the global kinematic vectors for a patient is made of 459 angle values (9×51). It has been first attempted to extract the critical values out of surgical database; however, as 11 surgery combinations are possible, the combination of only 40 patients in so many different categories is not significant. This is why analysis has been specifically focused on kinematic vectors [11], [15], [16]. The problem then faced is the large dimension of kinematic vectors. Several algorithms are available to reduce their size.

A polynomial approximation has been first used. With Matlab Software, the curves representing kinematic vectors can be displayed [11]. Three polynomial coefficients are obtained, representing the shape of the curve for each of the 9 articulations, ie every 51 points. In order to reduce the size of

459 values, Principal Component Analysis (PCA) has been used. However, the method is applied mainly on most discriminating pre-operative data based on values of their magnitudes before surgery. Keeping in mind that kinematic changes before and after surgery are the main project criteria, the approach has been oriented toward determination of critical values based on Gaussian distribution. The distribution of changes between pre-operative and post-operative data has been analyzed by comparing mean values and variances for each of these datasets. Thus the following coefficient **C** to separate elements of distributions has been established:

$$C = \frac{|mean(postop) - mean(preop)|}{(1 + \mathrm{var}(postop) + \mathrm{var}(preop))^{\frac{1}{2}}} \qquad (1)$$

Effectively it is verified that the smaller is the variance difference and the larger is the distance between the means, the larger will be the value of **C**. In this way, the 10 largest coefficients will characterize the 10 most discriminating values of the complete database (result verified by further research explained below). With vector data size reducedto 10, it is possible to apply it to discriminatingvalues and then to distinguish groups of patients.Using k-means function (available in Matlab toolbox) and after several iterations a stable result is obtained**.**

The program has been first randomly applied to two values among the ten most discriminating ones. Then, it was applied to both most discriminating values among the ten selected values (those with highest coefficient **C**). The result was clear and relevant. Graphically, the k-means result was only acceptable when used for both most discriminating values. No distinction between groups (try with 3 clusters) was possible except when the algorithm worked for values with the highest **C**. K-means program has been applied for right and left legs separately. Indeed, it is important to compare all right members together (respectively left members) to keep the gait analysis more precise.

The final result, throughclustering operation identifying closestpatient to studied patient X, is displayed and thecheck can begraphically performed as on Fig.1.

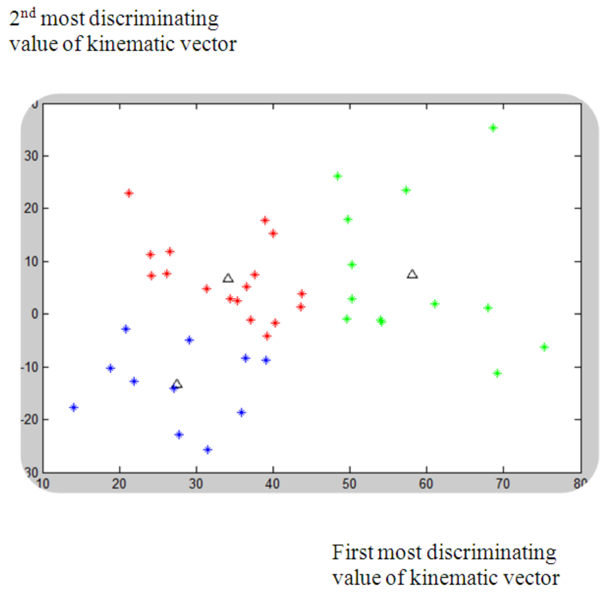


Fig. 1 Representation of k-means repartition of 40 patients based on the two most discriminating values of kinematic vectors. Triangles represent cluster centers and each color distinguishes a cluster

## III. Neural Network Analysis

Neural network is an application based on the operation of biological neurons [12]. It will be used here to predict the type of surgery to apply to a patient based on pre-operative kinematic data. Inputs are the pre-operative kinematic values and outputs are the suitable applicable surgeries, and connection is realized when synaptic weights which are internal neural network parameters are determined in learning phase by trial and error converging method [12]. In second synaptic weights test phase an average error rate is evaluated. To refine neural network application three different parameters can be adjusted: the learning step, the number of hidden layers and the number of neurons in layers. Depending on data dispersion, neural network is considered as already correctly working if error rate is about two times less than random one. In present case, parameters are

Learning step: $\mathbf{10^{-5}}$ ; Number of hidden layers: **1**; Number of neurons in layers: **20** (2)

With these values, the error rate averages to 12.5% and standard deviation is also 12.5% (4 times less than random error). It is thus possible to reliably deduce from collected patient pre-operative kinematic data rates the surgery to be applied to him.

## IV. 3-D Modeling

Once closest patient of initial database to actual patient has been found, the goal is to provide a 3D-representation of patient post-operative walk in order to show him how could be his walk after prescribed surgical operations. This process is split into two parts:

- Building a 3D avatar physically close to the new patient (weight, height, color of skin).
- Animating gait motion of this avatar using kinematics vectors given by k-means and the neural network [4].

For first part, there already exist software programs providing configurable 3D avatar such as MakeHuman. This software enables to create a 3D avatar in .mhx format. This type of format can be imported in Blender to animate it.

For second part 3D avatar has internal “skeleton” defining feasible rotations for each segment relative to each other, and which will be animated. Amongst the many methods to animate objects, BioVision's Hierarchical (BVH) files have been chosen.

```
HIERARCHY
ROOT Hips
{
  OFFSET 0.00 0.00 0.00
  CHANNELS 6 Xposition Yposition Zposition Zrotation Xrotation Yrotation
  JOINT Chest
  {
    OFFSET 0.00 5.21 0.00
    CHANNELS 3 Zrotation Xrotation Yrotation
    JOINT LeftShoulder
    {
      OFFSET 8 19.6109 2.86452
      CHANNELS 3 Zrotation Xrotation Yrotation
      JOINT LeftArm
      {
        OFFSET 12 1 0.681055
        CHANNELS 3 Zrotation Xrotation Yrotation
        JOINT LeftForeArm
        {
          OFFSET 19 0 -1.52608
          CHANNELS 3 Zrotation Xrotation Yrotation
          JOINT LeftHand
          {
            OFFSET 23 0 0
            CHANNELS 3 Zrotation Xrotation Yrotation
            End Site
            {
              OFFSET 10 0 0
            }
```

Fig. 2 Hierarchy in a BVH file

Fig. 2 shows how these files are build according to a well-defined hierarchy established by linking the relative position of a "son" member to the relative position of his parent member.

Relations are marked by brackets. The top of the hierarchy is the parent member of all other ones, and is named the ROOT. Inside, the following braces are the members which belong to this main member. Each of the sons is a JOINT. These sons can have sons too.

As shown in Fig. 3 there is a matrix which X lines and Y columns at the end of this file.X is equal to the number of frames composing the animation and each column represents a rotation angle of a member (ex: The third column represents the Z position off the root).

```
MOTION
Frames: 73
Frame Time: 0.0333333
-314.502000 89.939800 300.388000 7.366090 0.017673 138.919000 0.000000
0.000000 0.000000 -2.706800 1.419790 -2.877630 .....
-312.357000 90.240200 298.256000 7.429500 -0.347529 139.629000
0.000000 0.000000 0.000000 -2.203480 -0.131710 -3.227370....
-309.362000 90.708600 295.524000 8.097390 0.061340 139.097000 0.000000
0.000000 0.000000 -0.738719 -0.076886 -2.886380......
...
...
```

Fig. 3 Movement Data Matrix in a BVH File

Then the given kinematics vectors are injected into the corresponding columns. Once this file is created, the skeleton of the 3D avatar is linked to this BVH file in order to animate it using a Blenderadd-on named “Mocap Tool” with excellent realistic rendering.

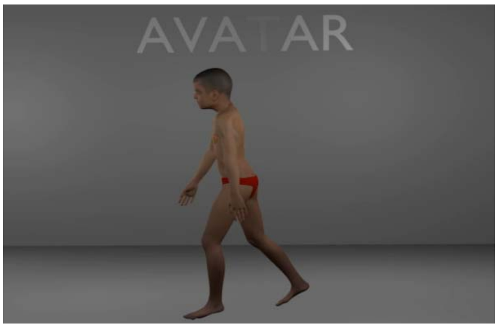


Fig. 4 3-D Avatar made with “Mocap Tool” of Blender

## V. Conclusion

Though necessarily very preliminary, present project has been showing so far the very powerful aid provided by adapted numerical tools to help both patients and medical personnel in the difficult task to pre-figurate the result of non-trivial heavy surgical interventions, and also in the decision to use them. Obviously large potential applications do exist in such an approach which could be named predictive rehabilitation. The method developed in present approach is essentially based on the observation that despite there are a large number of elements in patient state vector, it is already possible with classical tools to efficiently cluster patients in separate groups even when their number is relatively small (here 40). This suggests that effects of specific actions (soft physiotherapy or hard surgery) can be realistically predicted and visualized with quite a small error with larger database, as it can be reasonably extrapolated from present study where only 40 patient data have been collected. On the other hand, other parts of the process can also be improved. For neural network, by designing a more specific structure and optimizing itsworking parameters, it is possible to both obtain a lower dispersion error and to explore safely a larger set of patient situations. By linking neural network to present software, 3D modeling part will display a more precise post-operative model. As for 3D model, animation can be improved to better reproduce patient gait. Animation of body upper part and 3D model integrating patient facial recognition will give much realistic rendering of patient behavior with easier self-identification. Finally, Blender 3D model can be directly displayed from present software to end up with fully integrated package.

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