GENERATION OF GAIT PATTERNS WITH COMPETITIVE LEARNING

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ABSTRACT

A proper gait assessment in patients with knee or hip injuries strongly determines the diagnosis and consequently the evolution of the pathology, the quality of life of implanted patients, and the overall costs involved. Among the different strategies to clinically assess gait, 3D optical tracking provides a reliable and objective evaluation. This method involves state-of-the-art image analysis that performs anatomical measurements upon bony landmarks identified by markers attached to the patient. We show how this technology can be used to perform patients diagnosis and follow-up by grouping the results of gait measurement with a competitive neural network where the number of clusters is automatically determined.

INTRODUCTION

3D optical tracking has been extensively applied in recent years [Kawakami et al (1), Ghoussayni et al (2), Hallems et al (3), Kim and Eng (4), Manal and Stanhope (5), Alkjaer et al (6), Miller et al (7), Sadeghi et al (8), Churchill et al (9)], either with expensive commercial setups (1), (2), (3), (4), (7), (8), or with home-made cheap machinery (6), (9). Both approaches provide a reliable method to assess human gait in clinic and high performance applications (1), (2), (4), (5), (6), (8), (9).

This new field has been widely analyzed from the computer vision perspective, while data processing still remains open to researchers. Most efforts has been done with conventional statistical techniques, but the application of artificial neural networks in gait pattern identification has inspired very few works [Holzreiter and Köhle (10), Köhle and Merkl (11), Köhle and Merkl (12)].

The following results show that competitive learning is an alternative to SOM for gait patterns generation.

DATA ACQUISITION FOR GAIT ANALYSIS

Human gait was recorded in a room wide enough for the subjects to perform a gait start, a normal gait (including at least one complete cycle for each leg) and a gait end. MJPEG video was recorded from six synchronized PCs, each connected to a camera (1/500 sec shutter speed) as shown in Fig. 1. Each video stream contains a particular view of the gait, where the markers reflect the highest level of intensity of light in the image, since the scene is illuminated with six halogen focus (300 W), each on top of a camera. This arrangement maximizes the light returned by the reflecting material that covers the markers.

Dedicated software was developed to automatically obtain the 2D coordinates of the markers in every scene, that merged into 3D coordinates. This operation is performed using DLT (Direct Linear Transformation) coefficients [Bouquet (13)] generated upon a calibrating structure. This information allows a reliable three-dimensional reconstruction of the walking subject, and the precise computation of a number of measurement (distances and angles) that characterize human gait.

Fig. 1. Arrangement of cameras around the recording area where gait is performed.

In order to automatically detect the patient’s anatomical coordinates, 19 markers where placed on characteristic bony landmarks on the legs and hip of the patient (sacrum, up-front iliac bone, lateral-external area at the bottom of the thigh, frontal area at the bottom of the thigh, tibia -upper frontal area-, fibula -upper external area-, ankle, second metatarsal head, and heel). This markers are spherical, reflecting, hollow wood balls, 2.5 mm diameter, fixed to the skin with clinical sticking tape. The reflecting cover makes possible the automatic detection in the image (Fig. 2).

The experiment was performed on 166 patients, classified in three groups: healthy, pathologic, and implanted patients (with a PFC® Sigma™ prosthesis1)

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1 PFC Sigma is a trademark of DePuy Orthopaedics, Inc.
of either type simple, non-rotating anatomic, or non-rotating stable).
Dedicated software was coded to automatically obtain the 3D coordinates of each marker, and to compute anatomic measurements (distances and angles) upon thoses coordinates. The selected measurements were: pelvic obliquity, hip obliquity, knee obliquity, pelvic tilt, hip flex-extension, knee flex-extension, plantar flexion, pelvic rotation, and ankle rotation.

Fig. 2. Placement of markers on bony landmarks, and scenario for gait analysis, as recorded from the six cameras, where the markers are clearly identified in the image.

The evolution of the complete gait cycle comprises five different phases: early swing (which results in the maximum flexion of the knee joint), late swing (which is characterized by the heel gently touching the floor), weight acceptance (which occurs when the other leg is about to be lifted up and the body weight is shifted to the leg of interest), mid-stance (characterized by a straight leg with the foot flat on the floor), and terminal stance (in which the body weight shifts to the other leg and the heel is taken off the floor). In our experiments the complete cycle was analyzed for each measurement (Fig. 3), and principal components analysis was performed to reduce the dimensionality, resulting that knee flex-extension is the measurement that contributes the most to describe gait variability.

CLUSTERING WITH COMPETITIVE LEARNING

The problem of clustering a set of \( n \)-dimensional points (patterns) consists in finding a set of points in this space (prototypes) that minimize the overall distance of the patterns to their corresponding prototypes, i.e., the lowest distance from each pattern to the prototypes. Determining the number of prototypes and their location in this space is a NP-complete problem for a dimensionality equal or greater than two. Among other algorithms, competitive neural networks [Ahalt et al (14)] have been proposed to approximate solutions to the clustering problem for a fixed number of prototypes.

Competitive learning operates in a neural network by (1) selecting the closest prototype (winner weight vector) to the input pattern according to a given distance measure, and (2) moving the winner neuron’s weights to the input. The system is then defined in a formal way as a fully connected two-layers network, where the \( n \) inputs neurons \((x)\) store the input patterns, and the \( k \) output neurons \((y)\) raise a value according to the equation:

\[
y_j = \begin{cases} 
1 & \text{if } h_j = \max_i \{h_i\} \\
0 & \text{otherwise} 
\end{cases}
\]

(1)

where \( i \) ranges from 1 to \( k \), and \( h_i \) is the synaptic potential, given by the expression:

\[
h_j = \frac{1}{2} \sum_{j=1}^{n} w_{ij} x_j - \frac{1}{2} \sum_{j=1}^{n} w_{jj}^2
\]

(2)

and \( w_{ij} \) is the synaptic weight from input neuron \( i \) to output neuron \( j \). Considering \( w_i \) as the weights vector reaching output neuron \( i \), notice that the term \( w_i^T w_i / 2 \) has been introduced in the synaptic potential to warranty that \( h_j \geq h_j \iff \| w_i - x_j^2 \leq \| w_j - x_i^2 \| \), for all \( j \neq i \), where \( \| \) represents the Euclidean distance. Then, the winner neuron will be the one closest to the input pattern, \( x \).

Competitive learning is implemented by modifying the winner neuron’s weight vector according to this equation:

\[
\Delta w_{ij}(k+1) = \begin{cases} 
\eta \eta(x(k) - w_i(k)) & \text{if } i = r \\
0 & \text{if } i \neq r 
\end{cases}
\]

(3)

where \( r \) is the winner neuron, and \( \eta \) is the learning rate that controls the speed of convergence to the solution. The cumulative effect of this rule has the result of pushing the weight vectors to the centroids of the clusters, i.e., areas with high density of patterns. In the learned configuration \( w_i \) will store the coordinates of the prototype for cluster \( i \), as a new point in the \( n \)-dimensional space. The sample is then classified by assigning each pattern to the closest prototype.

As in many neural models, the main drawback of this learning rule is its sensitive dependence on initial conditions. The set of prototypes obtained strongly depends on the random initial value of the weights. Another important problem when applied to a sample of highly dimensional patterns is that the number of desired prototypes (output neurons) must be specified, even that no prior knowledge is available.

\footnote{Legs trajectories, pelvic tilt and pelvic rotation can also be obtained, but were not considered in this study.}
GAIT PATTERNS GENERATION

The application of competitive learning to clustering the gait cycle generates the prototypes that better fit the different patterns of gait. In this experiment, knee flex-extension was computed for a complete cycle of each of the 166 patients. The curves obtained for the three classes of patients are presented in Fig. 3(a).

![Figure 3(a)](image1.png)

Fig. 3(a). This comparison can also be checked by matching original and obtained prototypes (Fig. 5). Training the network to cluster the 166 patterns was done in real time on a conventional PIV-based computer.

Clustering with competitive neural networks is a powerful technique that generate prototypes of behaviour at a low computational cost. The application of this learning model to cluster gait patterns from 3D optical tracking measurements yields a number of gait patterns that precisely fit clinical assessment.

![Figure 3(b)](image2.png)

Fig. 3(b). Temporal evolution (1,000 samples) of a complete gait cycle. (a) Original classes (pre- and post-operatory, and healthy patients). (b) Result of clustering the sample into three groups.

Clustering this sample of patterns with equation (3) and a variable number of clusters results in a highly overall dispersion of the patterns (with respect to the closest prototype). Fig. 4 shows this dispersion graphically. We can appreciate that the reduction in overall dispersion from one to two prototypes is high, as it is when we increase to three prototypes. On the contrary, using more than three prototypes does not reduce dispersion significantly. Three is, indeed, the number of classes that we can clinically distinguish. The resulting groups of patterns are represented in Fig. 3(b), and they closely reshape the distribution in Fig.

![Figure 4](image3.png)

Fig. 4. Dispersion of the patterns with respect to the closest prototype (line, right axis), and reduction of overall dispersion in percentage with respect to the previous number of classes (bars, left axis).

![Figure 5](image4.png)

Fig. 5. Prototypes of original classes (continuous lines), and clusters obtained (dashed lines).

This clustering process demonstrates the existence of robust gait patterns, and confirms the clinically tested beneficial effects of total knee joint replacement, since the pattern of pre-operatory patients moves in the
direction of a healthy gait after surgery (post-operative pattern).
This method allows the dynamical computation of prototypes that can be used to assess gait, in diagnosis,
as well as in patient follow-up.

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