A New Approach for Quantitative Analysis of Inter-Joint Coordination During Gait

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***Abstract*—A new method for quantitative analysis of interjoint coordination at various walking speeds is presented. The model imposed a parametric relationship among lower limb joint motions (hips and knees) using the least number of parameters. An integration of different analysis tools such as harmonic analysis, principal component analysis, and artificial neural networks helped overcome high-dimensionality, temporal dependence, and nonlinear relationships of the gait patterns. The trained model was fed only two control parameters (cadence and stride length) for each gait cycle and predicted the corresponding gait waveforms. Based on the differences between predicted and actual gait waveforms, a coordination score, which ranged from 0 to 10, was defined at various walking speeds. The model was applied to eight patients with knee arthroplasty at different follow-ups as well as to eight healthy subjects, walking at three different speeds. The results showed that knee replacement and rehabilitation programs improved the coordination score. The technique provides an analytical tool that can be used as a routine test in the clinical evaluation of human gait abnormalities.**

***Index Terms*—Gait analysis, multi-joint coordination, parameterization.**

I. INTRODUCTION

HUMAN GAIT is a complex cyclical activity that involves coordination of many oscillating segments. Given the number of segments involved in human locomotion, there is an infinite set of possible trajectories determined both by the path as well as by the time at which each point on the path is reached. Accessing or computing such trajectories would require significant motor memory storage and computational power [1]. Coordination is a strategy chosen by the central nervous system (CNS) to restrict the set of possible movement trajectories and control the movements. A coordinated pattern is indeed the harmonious movement of independent body parts for efficient results. When motor coordination is specified at the link-segments or joint level it implies that the movement components are coupled together to produce efficient movement patterns. The CNS controls the movements by reducing the high number of degrees of freedom involved in a particular movement [2], [3].

Manuscript received April 4, 2006; revised May 3, 2007. This work was supported in part by the Swiss National Foundation under Grant FNRS 3200-064951 and Grant 3200B0-105880. *Asterisk indicates corresponding author.*

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Digital Object Identifier 10.1109/TBME.2007.901034

In the search for meaningful data reductions, several groups have tried to identify coordination patterns during walking [4]. The movements of lower limbs during gait are periodic and inter-joint dependent, so a relationship exists between the movements. Thus, a possible approach for studying gait coordination is to observe kinematic movements, as the “effect” of coordination, and summarize the relationships among multi-joint motions with few degrees of freedom [5]–[7]. However, quantitatively understanding and modeling of gait coordination has been a challenging endeavor. The main challenges can be summarized as high-dimensionality, temporal dependence, and nonlinear relationships of the gait patterns [8]–[10].

Previously, variable-variable plots have been used extensively to analyze the motion of one joint relative to the motion of another joint (angle-angle plot) and the angle of one joint relative to the angular velocity of that joint (phase-plane plot) [11]–[14]. Other authors have defined coordination as the ability to produce consistent patterns of interjoint coupling over multiple cycles. However, quantitatively understanding the interjoint coordination cannot be achieved with this methodology alone. Many authors employed frequency-domain or cross correlation analyses to evaluate the degree of coupling between pairs of joint angles [15]–[17]. These techniques are based on the assumption that linear relationships exist between two sets of kinematic time series data and identify the best fit linear transfer function between pairs of angles. Therefore, they are not particularly useful in determining the degree of linkage between body segments that have a nonlinear relationship.

Many authors applied principal components analysis (PCA) to examine temporal covariation between joint angles [4], [10], [18]–[20]. They could show that the multi-joint movements could be described as a linear combination of a small number of principal component (PC) curves or eigencurves. The results indicated that a strong coupling existed between joint movements. There are, however, limitations to the use of PCA, as it does not model nonlinear relationships among joint angles and interpretation of PC curves is heavily subjective as well.

Other authors modeled gait as a dynamical system and studied inter-joint coordination based on relative phase (RP) analysis [21]–[24]. RP represents the phasing relationships of a pair of interacting joints during a movement. This variable is calculated by subtracting the phase angles of the corresponding joints [25]. Values close to 0° indicate that the two segments are moving in a similar fashion or in-phase, while values close to 180° indicate that the two segments are moving in opposite directions or out-of-phase. Some authors utilized the variability of RP on the basis of inter-cycle standard deviation of ensemble relative phase curves as an index of coordinative stability [26]–[28]. Functionally, a low variability indicated a more stable relationship between the two joints' movements.

A common limitation of the past studies is that they could not provide a general model to quantify gait coordination at various walking speeds. In fact, people alter their gait patterns and their kinematic synergies when they walk faster or slower than normal speed to maintain their stability and minimize the energy cost of locomotion [29]. The alteration could also be present between gait cycles when it is considered as gait variability [30], [31]. Variability in the human motor system emerges from the multiple degrees of freedom inherent in the motor system [3]. A healthy system has also a certain amount of inherent variability, allowing for flexibility, adaptation, and learning. Nevertheless, a pathology may lead to changes in motor variability during walking. A lack of peripheral sensory information in neuropathic and elderly subjects, or having pain has been related to increases in variability found in locomotor patterns [31], [32]. It has been suggested that this increased variability is due to the diminished capacity of neuromuscular system to produce a functional gait pattern and it has been perceived as "error" in the neuromuscular system [33]. If the variability exhibited by the motor system is uncontrollable, that movement variability may not be beneficial and may lead eventually to a loss of stability and balance [34].

The objective of this study was to propose a new method to find a parametric relationship among multiple joint motions, while eliminating (or correcting for) inherent variability introduced by differences in walking speeds. The input parameters to the model are cadence and stride length that are controllable in human gait to adjust walking speed at each gait cycle. Then the model can predict or synthesize the movement patterns of the lower limbs at various walking speeds. The differences between predicted and actual gait waveforms are used to define a score for coordination.

II. Methods

A. Model Description

In this study, we considered a four-joint model of the lower limbs in the sagittal plane with two knees and two hips. The spatio-temporal patterning of the joint angles during a gait cycle can be expressed as

$$\mathbf{x} = [x_1, x_2, x_3, x_4] \tag{1}$$

where $x_j = x_j(t)(1 \le j \le 4)$ represents the time series of the left hip, right hip, left knee, and right knee angles, respectively. These flexion-extension angles were obtained using the methods presented in [35] and [36].

As defined earlier, coordination is the imposing or constraining of a relationship among multiple joint motions. In this model, we considered human gait as an automatic process that we feed with few control parameters such as cadence and stride length, and then it generates the trajectory patterns of the lower limbs. This process can be lawfully described as a function (F) that somehow captures the spatio-temporal patterning of the joint angles

$$\mathbf{x}(t) = F(\mathbf{c}; \varepsilon) \tag{2}$$

where $\mathbf{c}$ refers to the control parameters that are controllable in human gait to adjust the walking velocity. Walking velocity is the product of cadence and stride length, implying that a certain walking velocity can be achieved by different combinations of these two parameters

$$\mathbf{c} = [\text{Cadence, Stride Length}]. \tag{3}$$

The term ε in (2) refers to perturbations or uncontrolled events, arising from the multiple degrees of freedom, which could not be captured by the function F. There are, therefore, two aspects of (2): a deterministic aspect in which all the relevant kinematic information is specified uniquely by the values of $\mathbf{x}$, $\mathbf{c}$ and F, and a uncontrolled aspect ε that perturbs the systematically changing process. In other words, the process of improving gait coordination entails reducing the uncontrolled part.

The function F expressed by (2) can be identified by observing a sequence of gait cycles at different walking speeds and fitting a parametric model to the data set. Consequently, by feeding the model with control parameters, we can obtain a simulated trajectory of the joint angles. The definition of coordination by (2) implies that the system is able to reproduce consistent movement patterns of knee and hip angles over multiple cycles knowing the control parameters for each cycle. Therefore, the error (difference) between the actual and predicted trajectories for given values of the control parameters yields an estimation of the uncontrolled part ε

$$\hat{\varepsilon}_j(t, \mathbf{c}) = x_j(t) - \hat{x}_j(t, \mathbf{c}) \tag{4}$$

where $x_j(t)$ is the actual trajectory of joint j, and $\hat{x}_j(t, \mathbf{c})$ is the predicted trajectory with the given control parameter $\mathbf{c}$. This residual error, $\hat{\varepsilon}_j$, was used to define a score for coordination, since a low value of the residual error implies that the system is in possession of a lawful way of producing a wide variety of systematically related, functionally specific patterns over different control parameters.

We proposed a model to find a parametric relationship among multiple joint motions using the least number of parameters. An integration of different analysis tools such as harmonic analysis, PCA, and artificial neural network (ANN) was used to extract features hidden in the periodic patterns of gait, to reduce the dimensionality, and to model the nonlinearity of F. Fig. 1 shows the block diagram of the proposed method. The model consisted of two main parts: Training and Testing. Sections A-1–A-7 explain each of these blocks.

1) Calculating Control Parameters: The control parameters were obtained by calculating the cadence and stride length of each gait cycle (based on right heel strikes) using the algorithm proposed in [37] and [38]. Thus, for a sequence containing K gait cycles, the control parameter matrix could be expressed as

$$\mathbf{c}^{K\times 2} = [\mathbf{c}_k] \tag{5}$$

where $k(1 \le k \le K)$ is gait cycle number. The superscript $(K \times 2)$ indicates that $\mathbf{C}$ has two columns and K rows.

2) Time Normalization: In order to account for the temporal differences between strides, kinematic signals were time normalized by adjusting the gait cycles to have the same length [16], [39]. Time normalization of gait cycles was performed by

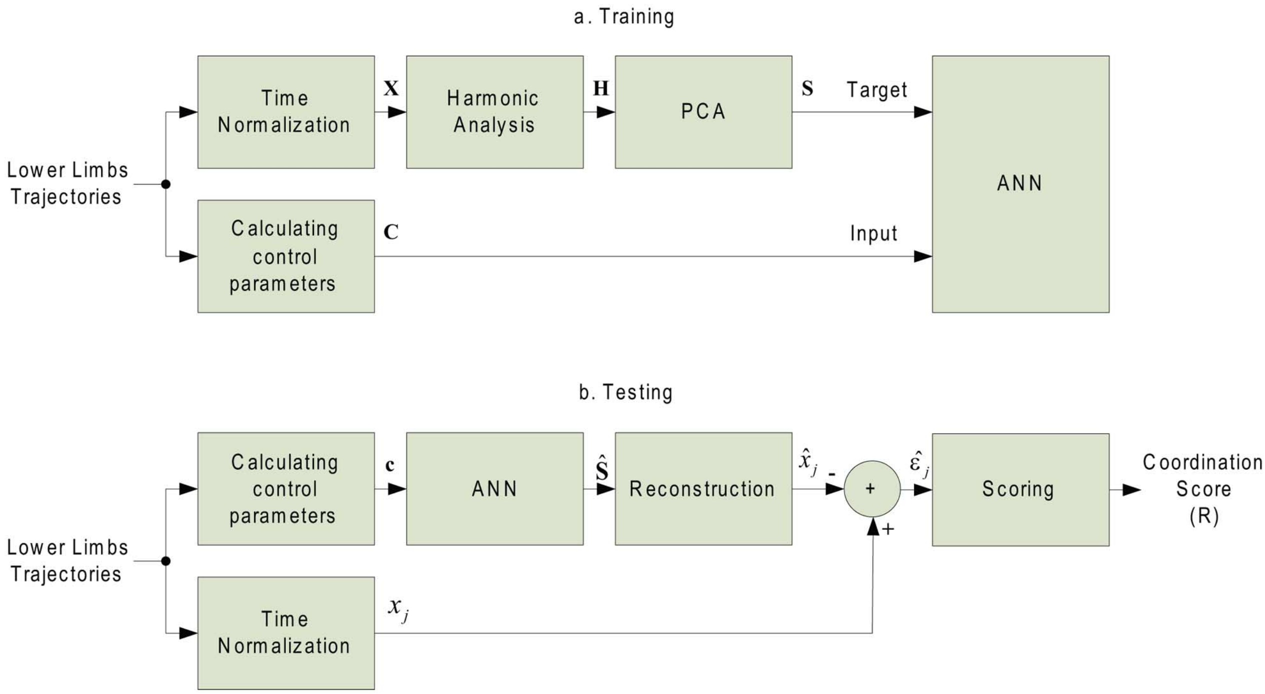

Fig. 1. Block diagram of the model. The model is trained using a set of (a) slow, normal, and fast gait data, and is tested for coordination using (b) a second set of slow, normal, and fast gait data.

rescaling each cycle time, based on right heel strikes, to a fundamental period length of 1.

The normalized waveforms were then resampled using a cubic spline interpolation to $N = 100$ samples per cycle. Therefore, for a sequence containing K gait cycles, the normalized angles of each joint could be expressed as a matrix with N rows and K columns

$$\mathbf{x}_j^{K\times N} = [x_{k,j}(t_N)] \quad (6)$$

where $j(1 \le j \le 4)$ is joint number and $t_N(0 \le t_N < 1)$ is normalized time. The whole data set could be expressed by concatenating the normalized angles of the four joints

$$\mathbf{x}^{K\times(4N)} = [\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4]. \quad (7)$$

The matrix $\mathbf{X}$, with K rows by $4N$ columns, indicates that the dimension of the kinematic patterns during each gait cycle is $4N = 400$.

3) Harmonics Analysis: Harmonic analysis was used as a feature extraction technique by parametric representation of the joint angles during each gait cycle. It is an optimum curve fitting technique that reflects also the periodic behavior of the gait waveforms. In general, a time-normalized joint angle with N sample points during a gait cycle can be expressed as

$$x(t_N) = A_0 + \sum_{n=1}^{N/2}((A_n \cos(2\pi n t_N) + B_n \sin(2\pi n t_N))) \quad (8)$$

where n is the harmonic number.

The magnitude spectrum of the hip and knee rotations drops to near-zero at around 5 Hz [40]. Accordingly, only the low order components of the Fourier series are required to reconstruct the signal [41]. The essential number of harmonics m required for 98% power of data reconstruction was defined as the minimum number of harmonics satisfying the condition that the sum of the relative amplitudes of each harmonic over total amplitude was greater than or equal to 0.98

$$\eta_m = \frac{\sum_{n=1}^{m}\sqrt{A_n^2 + B_n^2}}{\sum_{n=1}^{N/2}\sqrt{A_n^2 + B_n^2}} \ge 0.98. \quad (9)$$

The required number of harmonics m was calculated for each gait cycle in the database (all subjects, all trials, and all joints), and for consistency the maximum value was considered as the required number of harmonics for all analyses. Thus, $x(t)$ could be mapped to a vector of harmonic components

$$\mathbf{h} = [A_0, A_1, B_1, \ldots, A_m, B_m] \quad (10)$$

where $\mathbf{h}$ has $2m+1$ elements. Similarly, the Fourier coefficients of the data set $\mathbf{X}$ could be expressed by concatenating the harmonic components of $\mathbf{x}_j$ of the four joints during K gait cycles

$$\mathbf{H}^{K\times Q} = [\mathbf{h}_{k,1}, \mathbf{h}_{k,2}, \mathbf{h}_{k,3}, \mathbf{h}_{k,4}] \quad (11)$$

where $Q = 4 \times (2m+1)$.

4) PCA: We applied PCA to further reduce the dimensionality of the gait data by examining inter-cycle and inter-joint relationships of the harmonic components. PCA represented most of the variation of $\mathbf{H}$ using only a few decorrelated "principal components" (PCs).

The PCs are linear combinations of the original data, and a weighted sum of the PCs can exactly reconstruct the original data [42]. The PCs are ordered by the amount of variance they account for in the data, so that the majority of variation is captured by the first few PCs.

We examined the cumulative variance threshold criterion to choose the required number of PCs to keep. The cumulative variance accounted for by the first P principal components is given by

$$\eta_P = \frac{\sum_{i=1}^{P} \lambda_i}{\sum_{i=1}^{Q} \lambda_i} \tag{12}$$

where λ_i is ith eigenvalue which is equal to the variance of the ith PC. Assuming a cumulative variance threshold $\eta = 0.98, P$ is the smallest value for which $\eta_P \geq \eta$. Hence, the harmonic components matrix $(\mathbf{H})$ was transformed to the reduced space

$$\mathbf{S}^{K \times P} = [s_{k,p}] \tag{13}$$

where $s_{k,p}$ is the pth PC of the kth gait cycle.

5) ANN: The nonlinear relationship between inputs and desired outputs in F was modeled with an ANN. A neural network has the ability to generalize, meaning to be able to make reliable predictions for new inputs that are not in the training set. Therefore, the system could provide smooth interpolations for the untrained data set.

We implemented a two-layer perceptron architecture because of its good predicting power in supervised training mode for mathematical functional relationships. During the training phase [see Fig. 1(a)], the inputs consisted of the control parameters $(\mathbf{C})$, and the output layer (target) should produce the principal components of the gait waveforms $(\mathbf{S})$. The number of neurons in each layer was empirically determined, since they depend on the degree of nonlinearity and complexity of the model. Thus, a two-layer network with $3 \times P$ neurons in the first (hidden) layer and P neurons in the output layer was configured. The first layer had a Sigmoid transfer function to learn nonlinear and linear relationships; and the output layer had a linear transfer function to produce output values outside the Sigmoid range $(-1 \text{ to } +1)$. Then the neural network was trained by employing the Levenberg–Marquardt algorithm [43]. During the testing phase [see Fig. 1(b)], the outputs of the trained ANN provided an estimate of the PCs of the gait waveforms $(\hat{\mathbf{S}})$.

6) Reconstruction: In order to reconstruct the predicted trajectories in the time domain, first an inverse PCA transform was applied to the ANN outputs $(\hat{\mathbf{S}})$ to go back to the harmonics domain. Knowing the harmonics, the joint angles in time domain $(\hat{x}_j)$ were obtained through an inverse Fourier transformation.

7) Scoring: As shown before, the residual error expressed by (4) was used to define a score for coordination. First, the normalized root mean squared (RMS) error of each joint j during each gait cycle k was computed as

$$E_{k,j} = \frac{\left[\frac{1}{N}\sum_{t=1}^{N} \varepsilon_{k,j}^2(t)\right]^{1/2}}{\left[\frac{1}{N}\sum_{t=1}^{N} x_{k,j}^2(t)\right]^{1/2}}. \tag{14}$$

Since the error value grows with the amplitude of the joint rotation, the RMS error was normalized to the RMS of the actual joint rotation to obtain a dimensionless relative error.

Then a logarithmic mapping function was applied to give a coordination score between 0 and 10

$$r_{k,j} = r_{\mathrm{Max}} \frac{\log\left(\frac{E_{k,j}}{E_{\mathrm{Max}}}\right)}{\log\left(\frac{E_{\mathrm{Min}}}{E_{\mathrm{Max}}}\right)} \tag{15}$$

where $r_{\mathrm{Max}} = 10$ is a scaling constant to adjust the maximum score output, and E_{Min} and E_{Max} are constants chosen empirically to adjust the range of the normalized RMS error values. E_{Min} corresponds to the highest coordination score (minimum normalized RMS error), and E_{Max} corresponds to the lowest coordination score (maximum normalized RMS error). Logarithmic mapping nonlinearly compresses the high dynamic range of E, such that small values of error are used for scoring in more detail [44]. This score allows us to determine the coordination score of each joint.

Consequently, the overall coordination score during each cycle was defined as the average of coordination scores of each joint

$$R_k = \frac{1}{4}\sum_{j=1}^{4} r_{k,j}. \tag{16}$$

In order to evaluate the coordination scores at various speeds, the values of $r_{k,j}$ and R_k were calculated for each gait cycle k and then plotted versus the speed. Then a second-order polynomial (quadratic) curve was fitted to the data (r_j and R, respectively) to better represent and interpret the results. Additionally, the coordination scores (R_k) of each trial at slow, normal, and fast speeds were averaged over their gait cycles k to give an average score R for each gait trial.

B. Data Collection and Subjects

We applied our proposed method to eight patients, diagnosed with unilateral knee osteoarthritis waiting for a total knee arthroplasty, as well as to eight healthy subjects. The subjects (nine men, seven women, 68.7 $\pm$8.5 year) had given informed consent. The patients were tested preoperatively (baseline) and post-operatively at six weeks and six months. Each subject was asked to perform six walking trails of 30 m length at three different self-selected speeds: normal (trials 1 and 2), slow (trials 3 and 4), and fast (trials 5 and 6). Only steady-state parts of walking trials were used for analysis and the transient (initial and terminal) cycles were eliminated. Trials 1, 3, and 5 were used for training the model (ANN), and trials 2, 4, and 6 were used for testing coordination.

To capture lower limb motions, five sensor modules, each consisting two accelerometers and one gyroscope, were used. The sensors (dimension: $20 \text{ mm} \times 20 \text{ mm} \times 10 \text{ mm}$) were mounted on the sacrum, and both thighs and shanks. The sensing axes were adjusted in the anterio-posterior plane so that the motion in the sagittal plane could be measured. All signals were sampled at 200 Hz using the Physilog (BioAGM, CH) ambulatory system carried on the waist. Heel strikes were detected based on algorithm proposed in [38]. The method utilized shank sagittal angular velocities and searched for the first negative peak after the mid-swing phase. The detected peak was associated with a heel strike. The error in estimation of the heel strike events was less than 10 ms.

Statistical comparison of the results were made using paired Wilcoxon sign rank tests for comparison within patient groups, and independent Wilcoxon rank sum tests for comparison of patient group with the normal subjects. A value of $p < 0.05$ was considered significant.

Clinical examination was completed by the Western Ontario McMaster (WOMAC) Osteoarthritis Index [45] for each patient

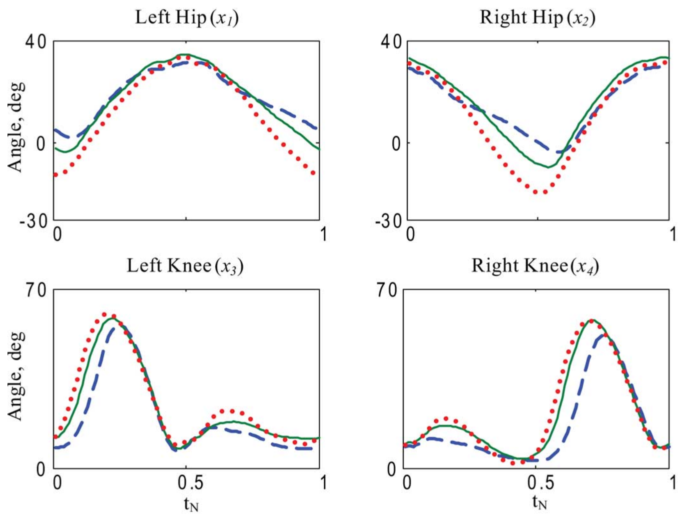

Fig. 2. Time-normalization of lower limb joint angles to gait cycle time. The start (0) and end (1) times correspond to heel strikes of right leg. The curves represent three typical gait cycles of a healthy subject (no. 1) at slow (dashed line), normal (solid line), and fast speeds (dotted line). The control parameters (cadence, stride length) of the selected cycles were $(0.60^{s-1}, 1.05\ \mathrm{m})$, $(0.85^{s-1}, 1.2\ \mathrm{m})$, and $(1.08^{s-1}, 1.41\ \mathrm{m})$ for the slow, normal, and fast cycles, respectively.

before and after surgery. The WOMAC consists of 24 Likertbox questions broken down into three domains: pain (five questions), stiffness (two questions), and physical function (17 questions). The sum of the WOMAC scores are then transformed to a 0 to 100 percent scale to facilitate comparison with other outcome measures. A WOMAC score of 0 represents the best possible health state. The WOMAC scores (mean $\pm$ std) of the patients at baseline was 58.5 ± 16.0, which significantly decreased to $37.9 \pm 9.1 (p = 0.008)$ and $23.0 \pm 10.5 (p = 0.008)$ at six weeks and six months follow up tests, respectively.

The coordination score was obtained by first normalizing the RMS of the residual errors using (14), and then applying the logarithmic mapping function using (15) to range the scale score between 0 and 10. Coordination versus speed was assessed by fitting a quadratic curve to the individual score of each gait cycle. The mean value of coordination scores at normal speed trials were compared with WOMAC scores by calculating correlation coefficient between the two scores.

III. Results

The data set $\mathbf{X}$ was created by first normalizing joint angles to gait cycle time, and then concatenating the normalized curves of the four joints using (7). Fig. 2 shows the result of normalization of three typical gait cycles of a healthy subject (no. 1) at different speeds.

The data sets $\mathbf{H}$ and $\mathbf{S}$ were created by making empirical choices to keep 98% of signal power in the harmonic analysis, and 98% of cumulative variance in the PCA. The required number of harmonics, m, was calculated by applying criterion (8) for each gait cycle in the database (all subjects, all trials, and all joints). For consistency, the maximum value $(m = 9)$ was considered as the required number of harmonics for all analyses. Thus, the total number of $4 \times (2m + 1) = 76$ parameters was required to reconstruct the motions of the four joints during a gait cycle. Subsequently, based on criterion (12), the required number of PCs to explain 98% of variance of the harmonic components $(\mathbf{H})$ was $P = 8$.

The model was trained for each subject using a set of slow, normal, and fast gait data. The second data set of slow, normal, and fast gait data was used for testing coordination. Lower limbs trajectories $(\hat{x}_j)$ and the residual error $(\hat{\varepsilon}_j)$ were obtained for all subjects during the test phase. Fig. 3 illustrates a typical result of predicting lower limb trajectories for patient no. 1 at baseline, who had very poor coordination.

The scaling constants in (15) were set to $r_{\mathrm{Max}} = 10$, $E_{\mathrm{Min}} = 0.01$, and $E_{\mathrm{Max}} = 0.15$. E_{Min} corresponds to the minimum normalized RMS error or the highest coordination score of a gait cycle in the data set (a healthy subject) and E_{Max} corresponds to the maximum normalized RMS error or lowest coordination score (a patient with poorest coordination). The mapping function was identical for all subjects.

Figs. 4–6 show the results of the scores versus speed for patient no. 1. Coordination score of each joint varied in an approximately quadratic fashion as a function of walking speed (see Fig. 4). The coordination score of the affected knee (left knee) indicated the least score for this patient (see Fig. 5). The overall coordination scores of the patient was very low, which increased at the two follow up tests at six weeks and six months (see Fig. 6).

The whole results of obtaining coordination scores of all subjects are summarized in Table I, which outlines the scores of eight patients $(P1$ to $P8)$ at three different follow up tests and eight healthy subjects ($H1$ and $H8$), as well as their mean and standard deviation. The scores of each trial at slow, normal, and fast speeds are reported separately. By comparing the scores of patients during follow up tests with baseline at each corresponding speed, all of the scores significantly increased. For instance, considering the patients' scores at normal speeds, the mean value of scores at baseline was 4.4, which significantly increased to $5.7 (p = 0.008)$ and $6.6 (p = 0.008)$ at six weeks and six months follow up tests, respectively. However, the score of the healthy subjects was significantly higher than the score of patients for all tests $(p < 0.05)$.

All subjects' scores during normal and fast speeds were higher than their corresponding scores at slow speed. For example, the mean scores of patients at baseline during normal and fast speeds were 4.4 and 4.0, respectively, that were higher than the mean score at slow speed (3.2) $(p < 0.05)$.

Fig. 7 shows the coordination scores (at normal speed) versus WOMAC scores for all patients at baseline and the two follow up tests. The correlation between the coordination scores and WOMAC scores was $-0.77 (p < 0.001)$.

IV. Discussion and Conclusion

In this study, we proposed a model to find the relationship between multiple joint motions during gait and estimate the trajectories of joint angles after a training phase with only two parameters: cadence and stride length. As trajectories with a small number of control parameters are properties of coordinated movements, our model expresses a new way to analyze quantitatively multi-joint coordination.

We used harmonic analysis to extract features hidden in the periodic patterns of gait, used PCA to reveal the reduced number

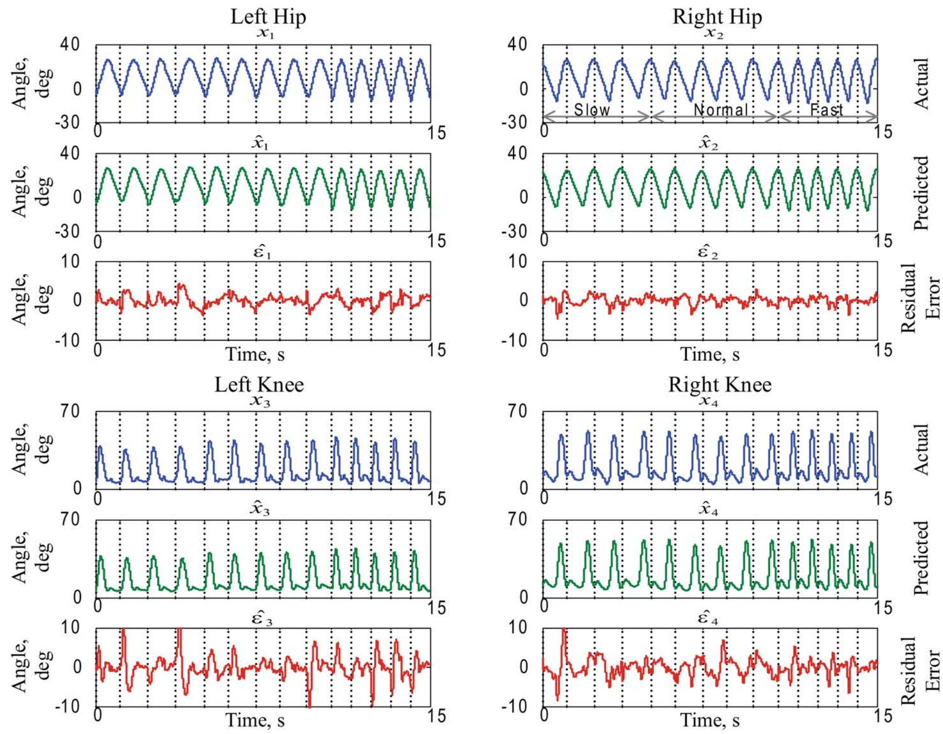

Fig. 3. Lower limbs trajectories (actual and predicted) and the residual error for patient no. 1 at baseline who had a very poor coordination. The vertical grids indicate right leg heel strike instances. The first four cycles were chosen from slow speed, the next five cycles were chosen from normal speed, and the last five cycles were chosen from fast speed trials. Note that the error scales are zoomed to -10.0 to 10.0 deg for better viewing.

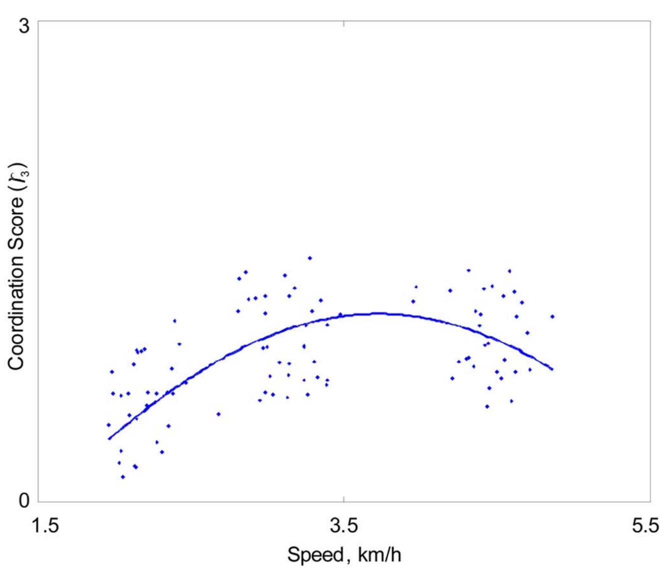

Fig. 4. Coordination score of affected (left) knee for patient no. 1 at baseline during three walking speeds (slow, normal, and fast). The dots indicate the scores $(r_k, 3)$ calculated for each gait cycle using (15). A polynomial curve was fitted to the data (r_3) to better represent and interpret the scores.

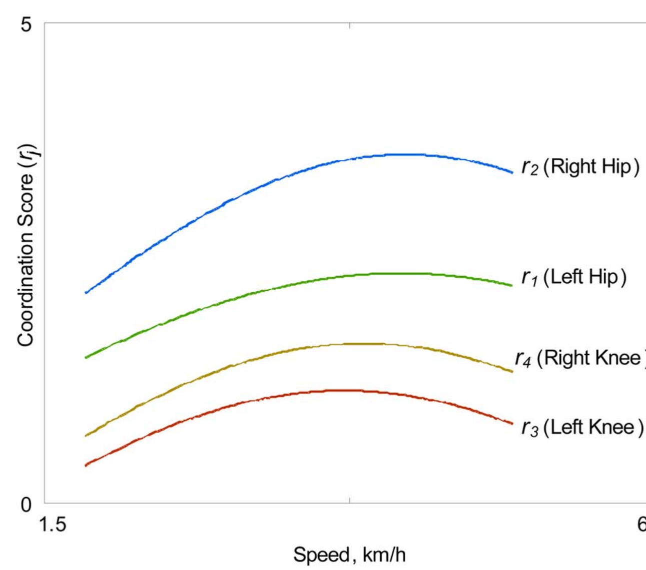

Fig. 5. Coordination score of each joint versus walking velocity (patient no. 1, baseline). The curves show the coordination score assigned to each joint versus walking velocity. The affected knee (left knee) has the least score (r_3).

of features evolving in gait coordination, and applied ANN to consider the nonlinear relationship existing between control parameters and angles.

Instead of harmonic analysis, higher order polynomials or other complex techniques might be used to parameterize the curves, but the number of the fitting parameters would increase, as they do not consider the rhythmic behavior of the joint movements, and the fact that the spectrum of the signals are low frequency (below 5 Hz).

Subsequently, PCA was a used to reduce the dimensionality of the harmonic components. Both harmonic analysis and PCA were necessary steps for dimensionality reduction. We first took advantage of the overall *a priori* known general features of the gait waveforms by extracting their parametric

TABLE I

COORDINATION SCORES OF EIGHT PATIENTS (P1 TO P8) AT THREE DIFFERENT FOLLOW UP TESTS, AND EIGHT HEALTHY SUBJECTS (H1 AND H8). THE SCORES OF EACH TRIAL AT SLOW, NORMAL, AND FAST SPEEDS, AS WELL AS THEIR MEAN AND STANDARD DEVIATION FOR EACH GROUP, ARE REPORTED SEPARATELY

Subject	Baseline			+ 6 Weeks			+ 6 Months		
	Slow	Normal	Fast	Slow	Normal	Fast	Slow	Normal	Fast
P1	1.4	2.3	2.1	3.7	4.8	4.6	5.2	6.5	6.5
P2	2.0	2.8	2.8	3.3	4.3	3.0	5.1	5.7	5.8
P3	3.5	4.0	4.1	5.6	5.8	6.1	5.6	6.7	6.9
P4	4.1	6.7	5.0	5.9	6.8	6.7	6.0	6.8	6.8
P5	4.4	6.0	5.5	5.4	6.2	6.0	5.8	6.4	6.6
P6	3.9	4.4	4.2	5.8	6.7	6.7	6.7	7.1	7.1
P7	2.7	4.5	3.7	5.2	5.6	5.9	6.0	6.7	6.9
P8	3.9	4.4	4.1	4.8	5.7	5.5	6.1	6.6	6.2
mean±SD	**3.2±1.1**	**4.4±1.5**	**4.0±1.1**	**5.0±1.0**	**5.7±0.9**	**5.6±1.2**	**5.8±0.5**	**6.6±0.4**	**6.6±0.4**
H1	6.1	8.1	7.6	-	-	-	-	-	-
H2	6.7	7.4	7.1	-	-	-	-	-	-
H3	5.0	6.6	5.1	-	-	-	-	-	-
H4	6.2	7.5	7.6	-	-	-	-	-	-
H5	7.3	7.4	8.4	-	-	-	-	-	-
H6	6.5	7.2	7.0	-	-	-	-	-	-
H7	6.1	7.8	6.6	-	-	-	-	-	-
H8	6.4	7.4	6.5	-	-	-	-	-	-
mean±SD	**6.3±0.7**	**7.4±0.4**	**7.0±1.0**	**-**	**-**	**-**	**-**	**-**	**-**

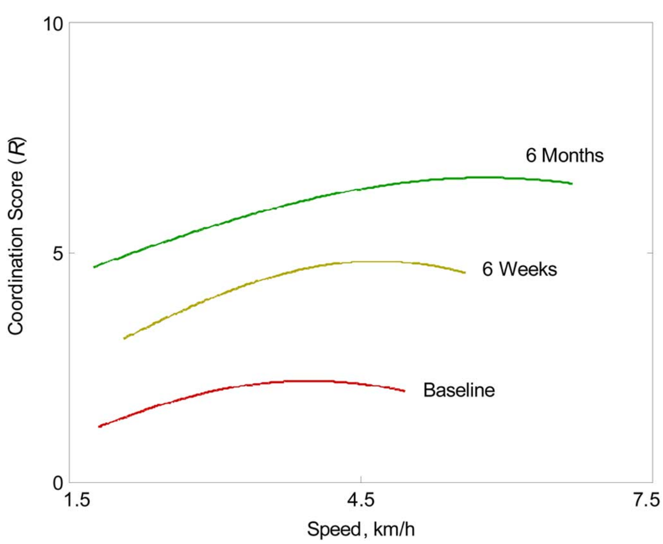

Fig. 6. Overall coordination scores of patient no. 1 at baseline and two follow up tests at six weeks and six months. The scores were calculated using (16).

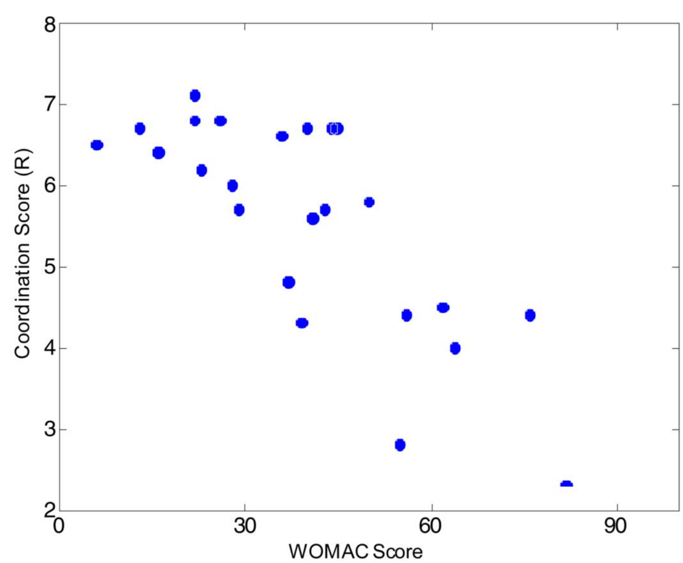

Fig. 7. Coordination score versus WOMAC score for eight patients at three follow up tests (baseline, and six weeks and six months after surgery). The coordination scores were calculated at normal speed. A lower WOMAC score indicate improvement.

features using harmonic analysis, and then applied a statistical technique (PCA) to decorrelate the parameters. Moreover, PCA could not be applied directly on the data set $\mathbf{X}$, because the transformation requires more gait cycles (K) than samples $(4N = 400)$.

Since PCA only detects linear relationships in the data, the ANN was used to model the nonlinear relationships among the PCs. It could estimate the PCs using only two inputs (cadence and stride length). A two-layer configuration was used, as it is appropriate for "function approximation" (or regression) problems, and it can learn any continuous functional relationship between inputs and outputs [46]. A three-layer network, however, was configured and tested. Nevertheless, the coordination scores did not change significantly in comparison with the two-layer set up. In contrast, a one-layer network was not sufficient for this purpose. We needed at least a layer with sigmoid transfer function (to learn nonlinear and linear relationships) and a linear output layer (to produce output values outside the Sigmoid range $(-1 \text{ to } +1)$).

The ANN was trained with Levenberg–Marquardt algorithm, as it appeared to be the fastest method for training small and medium size networks [43]. However, other training methods were tested and the results of coordination scores were not sensitive to the training algorithm.

We had several empirical choices in the model to select the number of harmonics and PCs to keep, and to select the number of neurons for the ANN. The choices were based on two criteria. First, the number of components and neurons should be sufficient for the model to discover the deterministic part of function F with an acceptable error. Therefore, the reconstruction error should be minimized such that the error (difference) between the actual and predicted angles (ε) carries only the uncontrolled or random events. Therefore, further increasing the number of components or neurons would not significantly reduce the residual error (ε). However, the data reduction error due to harmonic analysis and PCA were negligible compared to the residual error (ε). Second, the number of components and neurons should be kept at the acceptable minimum, in order to avoid memorizing the training data set, and learn to generalize to new motion patterns by smooth interpolations for the test data set.

The model was trained using one set of slow, normal, and fast gait data and then was tested using a second set of slow, normal, and fast gait data. We used the second data set to verify that the model could learn to generalize, rather than memorize the training data set. We compared the coordination scores obtained by the first (train, seen) data set with scores obtained by second (test, unseen) data set: the differences in scores were less than 5.3%. The small difference confirmed that the model was trained well.

We applied our proposed model to patients with knee osteoarthritis to delineate how pathology affects walking coordination. Knee osteoarthritis is marked by the progressive erosion of articular cartilage, subchondral sclerosis, and osteophytes growth at the joint margins. Individuals with knee osteoarthritis experience debilitating pain, joint laxity and instability [18], [19], [47]. In these patients, proprioception is partly impaired due to the lack of mechanoreceptors in the knee. The results suggest that knee replacement and rehabilitation programs improve gait function and coordination in individuals with knee arthroplasty. The significant correlation of the WOMAC scores with coordination scores was the external evidence for the clinical efficacy of the method. We also showed that, at each examination, the subject's scores during slow speed were lower than their corresponding scores at normal and fast speeds. This result is in accordance with [34], [48], as in general, if one tries to walk at an extremely slow pace, the movement is highly discoordinated, unstable and of poor efficiency. Similarly, Masani *et al.* found variability in ground reaction forces to be minimal at comfortable speed [49].

Several investigators have suggested that gait parameters change with walking speed, and differences in walking speed may therefore confound the results [8], [50]. Some researchers therefore administer paced walking, where either walking speed is controlled as on a treadmill or cadence is controlled by a metronome. Such constraints may affect natural walking behavior and thus influence gait characteristics particularly in patients with gait disorders. Some other researchers performed the measurement at different speeds and compared speed-dependent gait parameters at a normalized speed [50]. However, repeated measures are not always possible for disabled patients. In this paper, the coordination model can distinguish the variabilities due to changes in speed (cadence, stride length) and due to changes in kinematic patterns at a known speed. It considers the changes in walking speed as a deterministic (not random) part of gait.

Our method considers the difference between actual and predicted joint angle curves at each gait cycle to estimate the error. Therefore, it can be compared to existing methods based on variability of ensemble curves (obtained by calculating the point-by-point standard deviation across all normalized cycles for each data sample [8]). The main difference is that variability curves are sensitive to speed. For instance, the peak value of time-normalized knee angle does not occur at the same point (in normalized time) for different walking speeds (slow, normal, and fast), and it shifts to the left by increasing speed (see Fig. 2). Therefore, the variability due to changes in walking speed can hide other sources of variabilities in pathological gait. For instance, the average of variability bands (SD curves) for patient no. 1 at baseline, six weeks and six months were 3.1, 3.9, and 2.8 deg, respectively; and for healthy subject no. 1 were 3.0 deg, while for the same patient coordination scores increased after surgery but not reaching to the healthy score.

In the present study, we only examined the sagittal movements (2-D flexion-extension) of the hip and knee joints due to the limitations of the ambulatory device. Other researchers have suggested that a critical gait characteristic is the consistency of relative coordination between hip and knee movements [51], [52]. Although the results were satisfactory and could justify the method, future extension of this study should consist of incorporating full 3-D motions of the lower limbs including the ankle joint by using more sensors, since many patients with gait pathology compensate for difficulty in sagittal plane motions by using motions in other planes. Therefore, lack of 3-D analysis might have contributed to the low scores in the pre-op population.

The model is limited to steady state walking, so the transient cycles during gait initiation, termination and turning cannot be analyzed by the model. Moreover, the model needs many gait cycles (at least 100 cycles) at different walking speeds for the training phase. Most of motion capture systems such as camera-based systems are not suitable for this application, because their capture volumes are limited to a few gait cycles, and the patient cannot walk naturally or freely to reach his/her own steady state speed. Therefore, an ambulatory device should be used to capture the lower limbs motions.

Although the inputs of the model are only two control parameters defined in $\mathbf{c}$ (cadence and stride length), the ANN weights, obtained from angle waveforms during training phase, and actual joint angles during testing phase contribute in calculating the coordination score. However, kinematic patterns of the lower limbs can be affected by other parameters such as ground slope, terrain conditions, shoe type, load carriage, etc. Thus, during the test phase, the latter parameters or conditions should not change.

The proposed method, along with spatio-temporal gait analysis [37], [53], is being evaluated during routine clinical conditions to compare the outcome of fixed bearing and mobile bearing total knee arthroplasty. Although we applied the method to patients with knee arthroplasty, it can be used for assessment of other gait disorders, especially neurological disorders such as Parkinson's disease.

ACKNOWLEDGMENT

The authors would like to thank J. Gramiger and P. Morel in the design of the ambulatory system and C. Voracek, C. Pichonnaz, and A. Poloni for their assistance in collecting the data.

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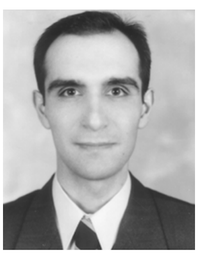

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