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A Postural Control Model to Assess the Improvement of Balance Rehabilitation in Parkinson's Disease

Zahra Rahmati, Saeed Behzadipour, Alfred C. Schouten, and Ghorban Taghizadeh

Abstract— **Studies have shown that balance and mobility in people with Parkinson's disease (PD) can improve through rehabilitation interventions. However, until now no quantitative method investigated how these patients improve their balance control. In this study, a single inverted pendulum model with PID controller was used to describe the improvement of forty PD patients after a 12-session therapy program, and to compare their balance with twenty healthy subjects. The Center of Pressure (COP) data were recorded in seven sensory conditions – on rigid and foam surface, each with eyes open and closed, and with visual disturbance; and stance on rigid surface with attached vibrator to the Achilles tendons. From COP data four Stabilogram Diffusion Function (SDF) measures were extracted. In order to find the appropriate model parameters (three control parameters and a noise gain) from the SDF measures, first model simulations were performed to tune an artificial neural network (ANN) which relates the SDF measures to the PID parameters, and second the trained ANN was used to find the suitable PID model parameters from the experimentally recorded SDF measures. Statistical analysis revealed that patients had lower control parameters and noise gain than healthy subjects; confirming reduced control ability and sensory information in PDs. Balance rehabilitation improved the patients' clinical scores, which is reflected in the increased control parameters (particularly in foam tasks), and noise gain (in tasks on rigid surface). The presented method provides a good and sensitive measure to describe functional balance and mobility in PD.**

I. Introduction

Parkinson's Disease (PD) patients are susceptible to a high risk of falls due to the related balance and movement disorders. Parkinson's disease is a progressive disease with the degeneration of special neurons of the nervous system. PD is marked with slow and imprecise movements (bradykinesia) and even frozen movement (akinesia), tremor, and abnormal crouched balance and gait patterns. Upright standing postural control of PD patients corresponds to a fundamental activity of their life [1]. Among the three different major therapeutic methods for PD – namely L-DOPA medication, Deep Brain Stimulation (DBS), and physical therapy – only physical exercises can prevent the neurodegeneration of further dopaminergic neurons [2]. Although medical and surgical treatments do significantly alleviate the disease symptoms, postural instability is less responsive to medications [1, 3]; and rehabilitative physical exercises could be an essential alternative for these patients. However, no established rehabilitation intervention protocol exists; and physical exercises are merely organized based on therapists' experience [1].

In order to optimize rehabilitation interventions, researches have put computational models forward [4]. *Computational Neurorehabilitation*, is an emerging area in which a computational model is developed to describe the dynamics of motor learning and as such guide the rehabilitation procedure. So far, computational neurorehabilitation models are primarily developed for the upper extremity. No study concerned the dynamics of motor learning during a balance rehabilitation program, while myriad of studies dealt with sensorimotor aspects of postural control model of healthy subjects [5]. In this study we developed a computational model to describe balance measurements in order for a better understanding of balance rehabilitation in PD.

Postural Control models of PD patients from an engineering viewpoint were mainly noticed in three major studies. Kim *et al.* [6] employed a full state feedback control scheme with a double inverted pendulum to explain PD patients' responses to the translational disturbance of the support surface. They found significantly smaller ankle gain and larger hip gain in PD subjects, compared to a healthy aged-matched group. Before, Maurer *et al*. [7] expressed the abnormal high-frequency sway of PD patients in OFF state, with an increase in the 'Loop Gain' and 'Noise Gain' level of a single inverted pendulum with PID control loop; in which the 'Loop Gain' decreased via L-Dopa and DBS treatments. In a recent study, Boonstra *et al*. [8] took a system identification approach to PD patients obtaining distinct FRFs (Frequency Response Function) for right/left sides of these patients, which exhibit significant different stability contribution role between the affected and the least affected body side. None of these studies have focused on the effect of balance rehabilitation of PD patients yet.

Several studies observed reduced motor ability in PD patients [8] [6, 9, 10]. Furthermore, most clinical trials reported enhanced functional balance and mobility for people with PD after physical exercises and rehabilitation interventions [11], suggesting that the CNS control effort is strengthened with rehabilitation.

The main scope of this study is to investigate how the effect of balance rehabilitation can be captured with an upright postural control model, and as such set the path for future computational neurorehabilitation models of upright stance. For this purpose, we measured the COP data of PD

Z. Rahmati and S. Behzadipour are with the Mechanical Engineering Department, and cross appointed with Djawad Movafaghian Research Center in Rehab Technologies, Sharif University of Technology, Tehran, Iran (phone: +98-21-66165542; e-mail: behzadipour@ sharif.edu).

A. C. Schouten is with the Department of Biomechanical Engineering, Delft University of Technology and University of Twente, The Netherlands (e-mail: a.c.schouten@utwente.nl).

Gh. Taghizadeh is with the School of Rehabilitation Science, Iran University of Medical Science, Tehran, Iran (e-mail: taghizadeh.gh@iums.ac.ir).

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patients under different sensory conditions before and after a balance rehabilitation program. We used Stabilogram Diffusion Function, SDF, to describe the measured COP data. According to [7], SDF parameters were picked for the PD characteristics evaluation, and a nonlinear regression tool – in the form of an Artificial Neural Network (ANN) – was used to relate these four measured SDF parameters to the control parameters of the suggested postural control model [12].

In the Stabilogram Diffusion Analysis – first proposed by Collins *et al.* [13] – a pre-recorded COP data is resampled with different time windows – known as Δt –, and the squared distance of the selected points are averaged (1). The SDF of human sway exhibits a special almost two linear region with different slopes (see Fig.4) denoted by D_s ('s' for short-term which corresponds to smaller Δt) and D_l (long-term with larger Δt). The two regions are distinctly separated with the *critical point* (with coordinates Δt_{critic} , Δx^2_{critic}) in which the two linear curves intersects (Fig.4).

II. Materials and Methods

A. Experimental Data

Participants

Forty PD patients (63.1 ± 12.1 yr) and twenty age-matched healthy subjects (63.8 ± 12.1 yr) participated in this study (Table I). The data were adopted from a previous clinical study [14]. Therapy was divided over twelve sessions. In this study, we used the data of the clinical and experimental assessments before and after the therapeutic sessions. The healthy subjects had no history of a balance disorder. PD patients were diagnosed by a neurologist. PD patients with the Modified Hoehn and Yahr stages ≤ 3 and Mini Mental State Examination (MMSE) > 24, who could walk independently for 10 m, were included. PD patients with any other neurological, orthopedic, visual, and vestibular disorders were excluded from the study. All participants provided written informed consent. The protocol was approved by the ethics committee of the Iran University of Medical Science.

TABLE I. Demographic Charachteristics of the Participants

Characteristic	Mean (Standard Deviation)		
	Patients (n = 40)	*Healthy (n = 20)*	*Significance Assessment*[a]
Age (years)	63.1 (12.1)	63.8 (12.1)	NS
No. of women (%)	7 (17.5)	4 (20)	NS
Height (m)	1.70 (0.080)	1.70 (0.078)	NS
Weight (Kg)	73.77 (13.50)	76.32 (12.65)	NS
Disease duration (years)	6.35 (4.85)		
Modified Hoehn & Yahr			
1	13		
1.5	10		
2	7		
2.5	10		

a. All statistical analyses were performed assuming an α level of 0.05, NS: non-significant

Procedure

Clinical and experimental assessments of the patients were done before the first session of therapy as well as after the last session. During the study, patients were in their ON state of dopaminergic medication, i.e. they used their normal L-DOPA medication. Healthy subjects were only assessed once, and only at the experimental tests.

Clinical Assessments

Clinical assessments were performed by a clinician. Clinical assessments include both functional balance and mobility tests; both showed significant improvement after therapy (Table II). Berg Balance Scale (BBS) [15] was used which includes 14 items each of which with a 0-4 score point. It includes both static and dynamic balance tests. Functional Reach (FR) was the next clinical test. The patients were instructed to stand next to a wall and position their arm at a 90 degree shoulder flexion with closed fist, and lean forward to the extent before taking a step using hip strategy. Assessor recorded the forward displacement of the metacarpophalangeal (MCP) joint. It was repeated three times and the average value was reported. BBS and FR were selected for the evaluation of the balance adequacy. Timed-Up-and-Go (TUG) test was also performed in which the patient stands up from the seated state, walks for 3m, turns around, walks back and sits down, and the elapsed time is measured for three times. The average was reported as a measure for the level of functional mobility. Barthel Index [16] was also taken– a self-report of ten preliminary activities of daily living and mobility, scored 0-100. Higher mark is associated with a greater level of living independently[14].

TABLE II. Clinical Outcome Measures of the Patients Before and After the Therapy Program

Clinical outcomes	Mean (Standard Deviation)		
	Baseline	*After therapy*	*Significance value*
Barthel Index	79.5 (11.8)	89.0 (11.2)	<.001
Berg Balance Scale	50.8 (2.9)	53.2 (3.2)	<.001
Functional Reach (cm)	26.87 (6.86)	30.69 (7.91)	<.001
Time Up and GO (sec)	9.11 (4.04)	7.70 (3.51)	<.001

a. All statistical analyses were performed assuming an α level of 0.05.

Experimental assessments

In addition to the clinical assessments, the spontaneous sway of subjects were recorded by measuring the trajectory of the Center of Pressure (COP) using a laboratory-grade force plate (Kistler Group type 9260AA6).

Participants had to stand in the seven following sensory conditions

- QSO: quiet stance on rigid surface with eyes open,
- QSC: quiet stance on rigid surface with eyes closed,
- QSV: quiet stance on rigid surface with a visual disturbance shown to subjects on a monitor in front of them,
- FO: quiet stance on foam surface with eyes open,
- FC: quiet stance on foam surface with eyes closed,
- FV: quiet stance on foam surface with a visual disturbance as described in QSV, and
- Vib: quiet stance on rigid surface while two 80 Hz vibrator were attached to subjects' both Achilles tendons.

Each condition was performed twice and each trail lasted for 70 sec with the sampling frequency of 1 kHz.

Data Analysis

The COP data of each patient in each task were down sampled to 100 Hz [7] and low-pass filtered (10Hz, 3rd order Butterworth). Before feature extraction of the Stabilogram Diffusion Function (SDF) from the filtered COP data, the first and last 5 sec of each trial were removed. Finally, the four SDF parameters (D_s, D_l, Δt_{critic}, Δx^2_{critic}) were calculated using the custom open source software programmed in MATLAB, following the method of Collins *et al.*[13] (1).

$$< \Delta y_p^2 >_{(m)} = \frac{1}{n-m} \sum_{i=0}^{n-m} [y(i+m) - y(i)]^2 \quad (1)$$

where, y_p is the COP position, n is the total number of COP samples, m ranged from 0 to 1000 (for Δt from 0 to 10 sec), and <·> symbolizes averaging.

B. Model Description

Peterka [12] manifested that a single inverted pendulum model with a PID controller can reproduce the typical two-part SDF diagram of human sway. Moreover, he performed a sensitivity analysis to indicate how the control parameters of the model are related to the four SDF parameters, implying that a relation exists between the PID control settings and the four SDF parameters. However, he did not propose a systematic method to define model parameters from the SDF measures which is indeed a non-analytical relation. We took the advantages of the nonlinear regression capability of artificial neural networks (ANN) to map the extracted SDF parameters of each subject to their set of matching PID control settings. In order to train the ANN, model simulations with feasible settings were carried out. Next, the SDF measures were calculated from the resulted COP of simulations; hence, providing a set of SDF measures with their associated known PID parameters.

Postural Control Model

Human postural control in anterior-posterior direction during quiet stance conditions was modeled as a single inverted pendulum, controlled by a PID controller and a time delay of τ_d in the sensory feedback loop, which mimics the role of the CNS, see Fig. 1. Aside from the active correcting ankle torque, via PID controller, the intrinsic damping and stiffness (B_{pass}, K_{pass}) of the ankle joint were considered as well:

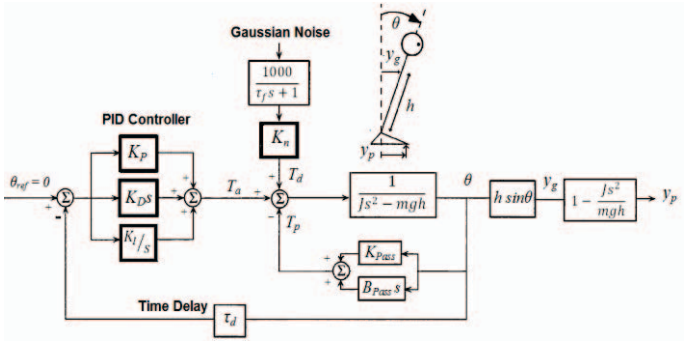

Figure 1. Postural control model of upright stance, a single inverted pendulum with the PID controller and time delay in the sensory feedback loop to represent the CNS.

$$J\ddot{\theta} = T_{Ankle} + mgh\sin(\theta) - K_{pas}\theta - B_{pas}\dot{\theta} \quad (2)$$

where, J, m, and h are anthropometric data of a subject, i.e. moment of inertia of the body around the ankle, mass, and the height of COM, respectively; and g stands for gravity. These parameters were set for a typical healthy subject with values as: m = 76 Kg, h = 0.87 m, J = 66 Kg.m^2 [12]. Passive elements in the model were set according to the averaged values identified by [17] for healthy subjects: B_{pass} = 1 N.m.s/deg , K_{pass} = 1.5 N.m/deg. In order to mimic the human spontaneous sway, a Gaussian noise was introduced to the control loop; while the desired reference point was set to 0 degree. The disturbance torque was also scaled by gain K_n. The Gaussian noise was low-pass filtered with τ_f = 20 s, and the sensory time delay was set to τ_d = 100 ms [12]. Further, the COP displacement was derived from the sway angle, assuming a single inverted pendulum dynamic [12] (3).

$$J\ddot{y}_g = mgh(y_g - y_p) \quad (3)$$

where, $y_g = h.\sin(\theta)$, and y_p is as in (1). The three control gain parameters K_P, K_D, and K_I, and the noise gain K_n were identified for each subject in each task.

The Neural Network Architecture and The Training Data

Regarding the nonlinear relation between the three control parameters and the four SDF sway measures [12], the ANN was designed to take the four SDF measures of each subject as input, and predict the fitting three parameters K_P, K_D, and K_I as output; thereby a model simulation in Fig.1 leads to the desired/input SDF measures (Fig.2).

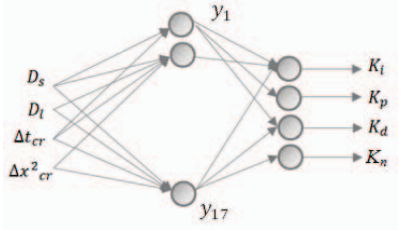

Figure 2. The Artificial Neural Network (ANN) architecture.

The ANN was developed in a feed forward multi-layer perceptron (MLP) scheme with one hidden layer, and 4-17-4 neurons in input, hidden, and output layers, respectively. As Fig.2 depicts, the proper peak-to-peak amplitude of the injected disturbance torque (in N.m, and denoted as 'K_n') was also determined by the network. In order to train the network in a supervised fashion, a dataset of known model parameters {K_P, K_D, K_I, K_n}, and their associated SDF measures {D_s, D_l, Δt_{critic}, Δx^2_{critic}} were needed. To this end, the model in Fig.1 was simulated for 625 settings of {K_P, K_D, K_I, K_n}; each corresponds to a grid point in the four dimensional space of parameters with the settings listed in Table III.

TABLE III. SETTINGS OF MODEL PARAMETERS FOR 625 (5^4) SIMULATIONS

Grid Number of Each Parameter	Model Parameters			
	K_P (N.m/deg)	K_D (N.m.s/deg)	K_I (N.m/deg/s)	K_n (N.m)
1	16	2.5	0	15
2	19.5	3.5	0.25	20
3	25	4.5	1	45
4	30	6	2	50
5	35	8	4	70

Among the 625 simulations, the unstable ones were removed from the training dataset; 591 data points remained.

Each simulation lasted for 60 sec. The resultant COP data, similar to the participants' COP data, were filtered and SDF measures were similarly computed. Therefore, a determined set of model parameters and their associated SDF measures were generated to be used for the network training. 70% of generated data were randomly assigned for training, 15% for testing, and 15% for validation. Learning was executed by the Error Back Propagation algorithm, using levenberg-marquardt minimization method, and with mean square error as the performance measure. All calculations were carried out in MATLAB Neural Network Toolbox v.8.1.

III. Results

A. Simulation Results

SDF Measures

Table IV shows the range of sway measures (SM) for the total data of both simulations and experimental evaluations; including seven conditions and both groups of healthy and PD subjects. The SMs' ranges from simulations covered the ranges of SMs from real data. This proves that the generated training data by simulation settings of Table III could adequately explain the behavior of both patients and healthy subjects, particularly in different sensory conditions.

TABLE IV. Ranges of Sway Measures in Simulations and Experimental Data, Including All Sensory Conditions

Group	SDF Measures [Min – Max]			
	D_s	D_l	Δt_{critic}	Δx^2_{critic}
Healthy	4.3 – 453.0	-3.0 – 49.7	0.70 – 2.50	4.8 – 715.9
Parkinson's Disease	3.3 – 578.3	-18.4 – 50.5	0.70 – 2.50	5.7 – 1103.1
Simulations	4.4 – 796.6	-17.8 – 110	0.74 – 2.50	3.3 – 1656.9

ANN Tuning and Verification

Considering the 591 data points to train the network in Fig.2, and in accordance to the general suggested rules for the number of neurons in the hidden layer [18], a number of 10 to 30 neurons are plausible. In this regard, the network were trained and examined for the hidden neuron numbers of {6, 9, 11, 13, 15, 17, 20, 22, 25, 30, 40}. The network was trained for 150 trials for each of these neuron settings. For each fixed hidden neuron number, the test and train performances of the networks of each trial were averaged over the 150 runs; shown in Fig.3. Furthermore, the best trained network among the 150 ones was also picked for each individual settings of hidden neuron and their test and training errors are plotted.

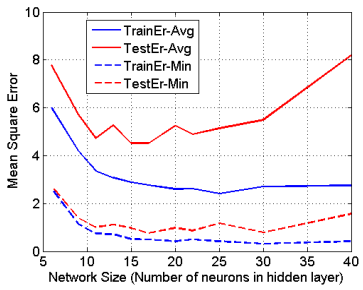

Figure 3. Perfromance of the network with different number of neurons in the hidden layer. Optimum number of hidden layer neurons = 17.

Fig.3 supports a fine-tuned network of hidden neuron size 17 which was then selected for the estimation of the model parameters of each subject. Fig.4 demonstrates two representative SDF diagrams of a healthy and a patient subject, as well as the reproduced SDF diagram of these subjects resulted from the model simulation with the parameters that predicted by the ANN; thus, verify the reasonable performance of the ANN for different patterns of SDFs in different tasks.

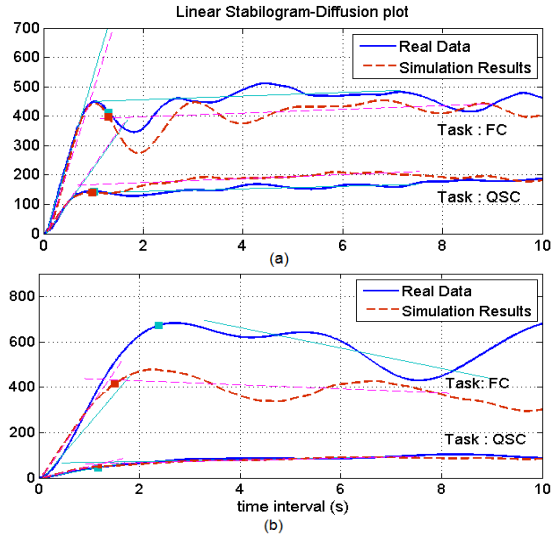

Figure 4. SDF diagram of two representative subjects and the reproduced SDF from model simulation with the predicted values of the ANN. a) Healthy subject (H5), b) Patient (P2).

B. Experimental Results

Table V summarizes the estimated model parameters. Fig. 5 also shows parameters K_P and K_n for healthy subjects (HS) and PDs before and after therapy sessions.

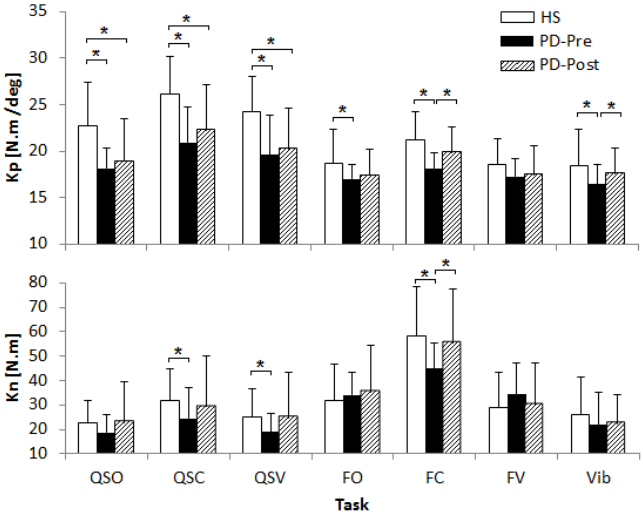

Figure 5. Control parameter K_P and noise gain K_n for healthy subjects (HS) and patients (PD) before (Pre) and after (Post) rehabilitation.

Inspecting the mean values in Table V and Fig.5, PD patients in Pre state illustrate reduced control ability and lower control parameters compared to the healthy group and in most of tasks. Moreover, PD group showed an increasing shift in all of their model parameters toward the healthy subjects after the rehabilitation intervention.

TABLE V. ESTIMATED MODEL PARAMETERS FOR HEALTHY SUBJECTS AND PATIENT GROUP BEFORE AND AFTER THE THERAPY IN ALL SENSORY TASKS

Task	Model Parameters, Mean (Standard Deviation)											
	Healthy subjects				*PD Patients before therapy*				*PD Patients after therapy*			
	K_P	K_D	K_I	K_n	K_P	K_D	K_I	K_n	K_P	K_D	K_I	K_n
QSO	22.8(4.5)	4.3(0.7)	1.7(0.8)	22.4(9.2)	18.1(2.2)*	4.1(1.1)	1.4(0.8)	18.7(7.5)	18.9(4.5)	4.3(1.3)	1.7(1.3)	22.8(16.7)
QSC	26.2(3.9)	4.9(0.9)	2.0(1.2)	31.6(13.2)	20.9(3.8)*	4.4(1.3)	1.7(0.9)	24.4(12.5)*	22.3(4.9)	4.4(1.4)	2.0(1.7)	29.4(20.5)
QSV	24.2(3.8)	4.9(0.6)	2.1(1.4)	25.1(11.6)	19.6(4.3)*	4.2(0.5)*	1.4(0.9)*	18.9(7.7)*	20.3(4.3)	4.3(1.5)	1.5(1.0)	24.7(18.9)
FO	18.7(3.5)	3.0(1.0)	2.4(1.3)	31.6(15.3)	17.0(1.5)*	3.0(0.5)	2.6(1.5)	34.2(9.2)	17.4(2.8)	3.7(1.5)	2.8(1.6)	35.4(18.8)
FC	21.3(3.0)	3.7(1.5)	2.6(1.4)	58.2(20.2)	18.1(1.6)*	2.7(0.9)*	2.1(1.7)	44.8(10.7)*	20.0(2.7)	3.9(1.6)	3.0(1.8)	55.5(21.9)
FV	18.5(2.8)	3.5(1.8)	2.9(1.7)	29.1(14.0)	17.2(1.9)	3.2(1.0)	2.2(1.5)	34.3(12.8)	17.4(3.0)	3.2(1.3)	2.5(1.7)	30.0(17.4)
Vib	18.4(3.9)	4.1(1.2)	1.7(1.0)	26.0(15.6)	16.4(2.1)*	4.6(1.5)	1.8(1.0)	22.0(13.1)	17.6(2.7)	4.0(1.3)	1.4(1.0)	22.3(11.7)

a. All statistical analyses were performed assuming an α level of 0.05. *Significant difference between healthy subjects and patients group at baseline.

C. Comparative Study

HS vs PD_Pre: While the estimated parameters from all tasks were pooled together, an independent t-test showed a significant larger values in HSs than in patient group at baseline for all four model parameters of {K_P (<.001), K_D (.025), K_I (.024), K_n (.029) – significance values in parentheses}. In particular, parameter K_P was significantly lower in patient group in all tasks except for FV, which was also significant with less probability (P = .079). Reduced K_P, K_D, and K_I in PDs is in-line with reported reduced control effort and ability in these patients [9, 10].

In addition to control parameters, K_n also demonstrated a significant difference between HSs and PDs, in pooled-task study and specifically in the ones with eyes closed, i.e. QSC and FC. Parameter K_n, which shows strong correlations with position and velocity-related sway measures [19], represents a kind of scaling factor for the total spontaneous sway behavior. Smaller K_n in PDs further emphasizes the reduced sway amplitude and velocity (more rigidity and freezing behavior) in PD patients. Patients with closed eyes have to mainly rely on their proprioceptive and vestibular information; however, the vestibular data in small angles is non-significant [17]. Moreover, the proprioceptive feedback in PDs is imperfect [20].Thus, patients with closed eyes have less sensory information of their standing state and therefore display much smaller sway amplitude than healthy subjects; which was reflected by significantly smaller K_n. K_n is also known to be an indicator of the noise level in the sensory loop [7, 19]. From this perspective, in contrast to what was put forward in [7, 19], the noise level of sensory system can be a measure of the power of sensory input rather than a perturbing noise in the feedback signal.

Patients, Pre vs Post: Table VI shows the statistical comparisons for the patients before/after the therapy sessions.

TABLE VI. STATISTICAL RESULTS OF PATEINTS' IMPROVEMENT

Tasks	Significance Value (Before Therapy vs After Therapy)			
	K_P	K_D	K_I	K_n
Pooled all tasks	.001*	.045*	.039*	.012*
Pooled rigid surface tasks (QSO + QSC + QSV)	.061	.565	.099	.013*
Pooled foam tasks (FO + FC + FV)	.018*	<.001*	.039*	.229

a. All statistical analyses were performed assuming the an α level of 0.05. *Significant difference.

In order to obtain a general insight into how the patients' performance altered after the intervention, a paired t-test was performed while the whole tasks were pooled together; in other words, evaluating the progress of these patients in their averaged functionality, including all task responses (first row in Table VI). The results revealed a significant difference in all model parameters, particularly K_p and K_n with remarkable growth after rehabilitation; confirming the improved control ability (K_P), and enhanced encoding of the sensory signal (K_n).

In view of the fact that PD patients showed more deficits in the correct usage of proprioceptive feedback data rather than the two other visual and vestibular information [20], the pooled data of the three tasks on rigid surface (QSO+QSC+QSV) and the pooled data of the three tasks on foam (FO+FC+FV) were also separately compared before and after the therapy (Table VI). Findings indicate a boosted K_n only for tasks with stance on rigid surface, and not a marked changes in the three other control parameters in these tasks. However, the mean values of the three control parameters showed increment; so, their statistical significance can appear after more therapy sessions with sustained lasting influences.

Unlike the tasks on rigid surface, control parameters – K_P, K_D, K_I – showed significant enhancement while patients stood on foam after the therapy program. This can be justified by the reason that standing on an unstable foam evokes more controlling aspects of human postural control system rather than a simple task of stance on rigid surface which is easier to perform (in lower stages of disease). In contrast to control parameters, K_n has no effect on the frequency response of the human postural control system, and merely associates with the scale of sway range and velocity. Augmentation of K_n in tasks of stance on rigid surface explains the developed functional mobility which was remarked in improved clinical assessments. Nevertheless, K_n showed non-significant changes in foam tasks. Standing on foam incites low-frequency sway which dominates the general range of motion and is typically in the same order for groups of people; since otherwise significant larger motion on foam for a group can cause instability. thus, K_n is not supposed to show a remarkable change for tasks on foam. Among the three control parameters with significant improvement after rehabilitation for tasks on foam, K_D displayed higher increase with P<.001, expressing an

additional improvement in the patients' sensitivity to the velocity feedback.

IV. Discussion

Findings of this study suggest that the four SDF measures can establish an almost comprehensive description of the COP data. Maurer et al. [7] found the four parameters of SDF sufficient to explain the altered postural behaviors of PD patients in ON and OFF states. Their valuable Principle Component Analysis on fifteen prevalently examined sway measures of the COP data indicated that they show three principal aspects of human sway: displacement/velocity/and frequency-related measures [19]. According to this study, the four SDF parameters are nicely distributed within these three groups: Δx^2_{critic} and D_l are representative of displacement-related measures, D_s is correlated with velocity parameters, and Δt_{critic} accounts for the frequency domain measures of the COP. All these COP features stem from the functioning of the CNS which is represented by PID parameters in our model. Our study showed that the PID parameters can be identified from the four SDF measures. Further, an ANN can provide an adequate mapping tool to relate the four SDF measures to their appropriate matching PID parameters.

Our findings also showed that the static COP data of patients with Parkinson's diseases is still rich enough to distinguish PD impairments. Except the article of Maurer *et al.* [7], all previous studies on computational models of PD patients' balance deficits had focused on reactive responses [6, 8]. On top of that, static posturography has the capacity to reflect the way that these patients improve through rehabilitation interventions. Clinically developed functional balance and mobility outcomes (Table II) which are the pivotal reports for these patients' improvement after rehabilitation were quantitatively explained by an inverted pendulum model and a PID controller. In this regard, three control parameters K_P, K_D, and K_I, showed a significant increase after rehabilitation in tasks on foam which demands higher control ability. Indeed, theses parameters' enhancement is what clinicians observe as boosted functional balance in these patients after therapy programs. On the other hand, significant growth of noise gain (K_n) in tasks with simple stance on a rigid surface corresponds to the upgraded functional mobility from clinical viewpoint. Additionally, an amplified K_n for patients after therapy – while the control parameters were almost unchanged – is an index of the extent to which they correctly encoded the sensory signal.

Despite the interesting findings in the current study, further detailed investigation on the changes of K_I and K_D parameters as well as the differences of tasks still remained for the future. Furthermore, the proposed method needs to be generalized to include subject-specific mass and height; however, it showed NS differences between groups (Table I).

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