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Test and Validation of a Smart Exercise Bike for Motor Rehabilitation in Individuals with Parkinson's Disease

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Abstract

To assess and validate the Smart Exercise Bike designed for Parkinson's Disease (PD) rehabilitation, forty-seven individuals with PD were randomly assigned to either the static or dynamic cycling group, and completed three sessions of exercise. Heart rate, cadence and power data were captured and recorded for each patient during exercise. Motor function for each subject was assessed with the UPDRS Motor III test before and after the three exercise sessions to evaluate the effect of exercise on functional abilities. Individuals who completed three sessions of dynamic cycling showed an average of 13.8% improvement in the UPDRS, while individuals in the static cycling group worsened by 1.6% in UPDRS.

To distinguish the static and dynamic cycling groups by biomechanical and physiological features, the complexity of the recorded signals (cadence, power, and heart rate) was examined using approximate entropy (ApEn), sample entropy (SaEn) and spectral entropy (SpEn) as measures of variability. A multiple linear regression (MLR) model was used to relate these features to changes in motor function as measured by the UPDRS Motor III scale. Pattern variability in cadence was greater in the dynamic group when compared to the static group. In contrast, variability in power was greater for the static group. UPDRS Motor III scores predicted from the pattern variability data were correlated to measured scores in both groups. These results support our previous study which explained how variability analysis results for biomechanical and physiological parameters of exercise can be used to predict improvements in motor function.

Index Terms

Smart exercise bike; Parkinson's disease motor function; movement disorders; neurorehabilitation; signal processing; variability analysis; active assisted exercise; UPDRS

I. Introduction

Parkinson's disease (PD) is a chronic, progressive neurological disorder, which affects approximately 7 to 10 million people worldwide and around one million people in the US, and is characterized by loss of dopaminergic neurons in the brain [3, 6]. The main symptoms of the disease are primarily movement related and include tremor or shaking, muscle stiffness and rigidity, and slowness of physical movements (bradykinesia). With the progression of PD, both motor and non-motor symptoms often lead to limit independence and increase the reliance on caregivers and the healthcare system. The economic impact of PD, including treatment, social security payments, and lost income from inability to work, is estimated to be nearly \$25 billion per year in the United States [15]. There is no known cure for PD. The accepted treatment is medication (e.g. levodopa) and in some cases surgical intervention (e.g. deep brain stimulation). These treatments typically mask the symptoms and do not slow progression of the disease, often have undesirable side effects, are costly, have diminishing effectiveness as the disease progresses, and can introduce additional health risks.

Recent studies in rehabilitation of patients with PD have shown that cycling can reduce the symptoms of the disease [2-7]. Studies with animal models have shown that high intensity exercise can promote neural plasticity and neuroprotection against dopaminergic cell loss [13]. Several studies in humans have revealed that high intensity treadmill training [11, 12] and high cadence cycling [1, 2, 3, 6, and 7] can improve motor function. Ridgel [3, 5, and 6] and Alberts [7] have shown that high cadence cycling can result in significant improvement in motor symptoms as measured with the Unified Parkinson's Disease Rating Scale (UPDRS) Motor III test. In [3], a novel approach was introduced to increase exercise intensity in individuals with PD referred to as forced exercise. This approach used a stationary tandem bicycle and an able-bodied cyclist (trainer) to assist individuals with PD to pedal at a cadence between 80-90 RPM (revolutions per minute). This high-cadence cycling was roughly 30% faster than they were able to pedal on their own at a self-selected rate that was determined during baseline evaluation. Pedal crank mounted power meters measured the power and cadence of the individuals with PD as well as the trainer during each exercise session. High-cadence tandem cycling resulted significant reduction in motor symptoms characteristic of people with PD as measured with standard motor performance tests (e.g. UPDRS). In particular, tremors and bradykinesia were significantly reduced. These improvements were global in that upper extremity motor function was enhanced after this lower extremity exercise. The observed global improvement was supported by fMRI data that showed increased levels of activation within cortical structures such as the supplementary motor area [7]. These findings suggest that high-rate tandem cycling may facilitate central motor control processes in PD riders. If accelerated cycling therapy proves

to be an effective therapeutic aid, this may permit altering the traditional treatments prescribed to individuals with PD thereby reducing the dependence on medications.

Recently, we analyzed patient and exercise data from individuals who completed an 8-week intervention of either single or tandem cycling [3, 7]. This study showed that temporal variability or lack of predictability in cadence, heart-rate and power signals during cycling are directly related to improvement or worsening in motor function in PD patients, and the amount of variability in these signals is a predictor of improvements in UPDRS Motor III scores [2].

Based on our findings published in [2], we have designed and developed a single-rider smart exercise bike that can be used for clinical studies and research in PD rehabilitation [1, 4]. An overview of the Smart Exercise Bike is presented in the next section. Details of the hardware, electronics, software, and control algorithms are described in [1] and [5]. The bike can accurately control the rider's experience at an accelerated pedal rate while capturing real-time performance data. Two main control algorithms have been developed for the bike, referred to as static mode (inertia load) and dynamic mode (speed reference). In the speed reference mode, the bike has the capability to run at a specified speed while providing the required variability in pedal speed. Speed variability has been shown to be an important factor in UPDRS improvement based on our previous findings [2].

In order to test the effects of exercise with these two types of control, forty-seven individuals with PD were recruited in an IRB-approved study at Kent State University under the direction of Dr. Ridgel. Individuals selected for the study were randomly assigned to either the static or dynamic cycling group. Each test subject completed three 40-minute exercise sessions every other day over a period of one week. Heart rate, cadence and power data were captured and recorded during each exercise session. The UPDRS Motor III test was administered in double-blind tests by a trained neurologist. This test was administered to each patient before and after the three exercise sessions in order to evaluate the effect of the exercise regimen.

To distinguish the static and dynamic cycling groups by biomechanical and physiological features, we have studied the variability/predictability of the recorded signals (cadence, power, and heart rate) using approximate entropy (ApEn), sample entropy (SaEn) and spectral entropy (SpEn). Results from these computations were used in a multiple linear regression (MLR) model to relate these features to improvements in motor function as measured by UPDRS Motor III scale. The variability analysis results are consistent with the results we previously published describing the changes in motor function observed in PD riders following voluntary (single) and forced (tandem) cycling experiments [2].

II. System, Materials and Methods

A. Overview of the Smart Exercise Bike

As stated earlier, to investigate the important role of tandem cycling in rehabilitation for people with Parkinson's disease, a novel exercise bike has been designed and fabricated based on the operating paradigm of a tandem bike (Fig. 1), using the results of the research

in [2]. The framework for the smart single-rider exercise bike is a commercial bike chassis equipped with commercially available motor and control equipment. This novel design incorporates high-performance drives and controls and a low-inertia, power-dense servomotor to form a flexible and adaptive platform to support clinical research studies of exercise for people with Parkinson's disease.

The Smart Exercise Bike includes two control algorithms that provide the ability to operate the bike in either the static (inertial load) mode, or dynamic (speed reference) mode while capturing operating data such as rider heart rate, cadence, and power at a high sampling rate. The static mode operates the bike as a regular exercise bike with a programmable resistance (load). In dynamic mode, the bike operates at a user defined cadence set-point with programmable load fluctuations that introduce cadence variations. The bike is equipped with a user friendly HMI employing an easy to read color touch screen. This integrated control and display system records critical rider and bike conditions and allows the rider to set required riding session parameters such as cadence set point and load. The completed system of the Smart Bike is shown in Fig. 2.

B. Patient Testing and Data Collection Using The Smart Exercise Bike

To test and validate the effectiveness of the exercise bike presented in [4], forty-seven individuals diagnosed with Parkinson's disease completed three cycling sessions over a one week period riding the smart bike, and were evaluated for changes in motor function after the exercise sessions were concluded. Each study participant was randomly assigned to use either the static or dynamic control mode during bike operation and they were able to successfully complete three 40-minute cycling sessions. Demographic data was analyzed using independent sample t-tests and there were no significant differences between the static and dynamic cycling groups, demonstrating an acceptable level of homogeneity across the groups (Table I). The static group included 16 males and 7 females, and the dynamic group included 12 males and 12 females.

Pedaling cadence and power exerted by the patients in each group were measured and recorded by a programmable logic controller (PLC) which also controls bike operation and the display screen. A wireless chest-worn heart rate monitor (Polar Electro, Lake Success, NY) transmitted rider heart rate data to the PLC during bike operation for storage and subsequent analysis. In order to examine the captured raw data for the static and dynamic control modes, the mean and standard deviation of the “heart rate”, “power” and “cadence” signals for all tests were calculated (Table III). Dynamic and static cycling modes resulted in similar subject self-assessments of RPE (Rating of Perceived Exertion). However, there were significant differences in cadence, power, torque and heart rate observed (Table II). Interestingly, individuals in the static cycling group showed a lower cadence but higher power, torque and heart rate than riders in the dynamic cycling group.

C. Motor Function Assessment

The Unified Parkinson's Disease Rating Scale (UPDRS) Motor III exam was administered to each participant by a blinded neurologist (B. Walter). Assessments were performed just prior to the start of the first exercise session and two days after completion of the third exercise

session (Table III). The difference in UPDRS Motor III scores between these two time periods was calculated and used in later analysis. A negative change in score represents improvement while a positive change indicates worsening of motor symptoms.

D. Biomechanical and Physiological Feature Analysis

To study the difference between the static and dynamic cycling groups, we have analyzed the recorded signals (cadence, power, and heart rate) using the approximate entropy (ApEn), sample entropy (SaEn) and spectral entropy (SpEn) to quantify variability/predictability in these signals. Both ApEn and SaEn quantify the predictability (or regularity) in a time series, and are useful in quantifying differences in health and disease [8, 9]. ApEn is a regularity statistic that quantifies the unpredictability of temporal fluctuations in a time series such as an instantaneous heart rate time series, $HR(i)$. The presence of repetitive temporal patterns in a time series renders it more predictable than a time series in which such patterns are absent. ApEn quantifies the possibility that similar patterns of observations will not be followed by additional similar observations. A time series containing many repetitive patterns has a relatively small ApEn. Alternatively, a less predictable (i.e., more random or less time-correlated) time series will have a greater ApEn. SaEn is a modification of ApEn to remove the potential bias in ApEn by eliminating self-matches in the computation. The values for ApEn and SaEn computed for each dataset are nearly the same, so further analysis focused on the SaEn computations.

SpEn is another variability measure that quantifies the distribution of frequency content in a time series. The interpretation of SpEn (in the frequency domain) is very similar to ApEn and SaEn (in the time domain).

ApEn, SaEn and SpEn for “heart rate”, “power” and “cadence” signals were computed for all data sets for each person. The computed values were used to quantify the variability of both temporal and frequency domain patterns. The mean of these parameters for three exercise sessions were computed for the static and dynamic groups and have been used to distinguish between the two groups. These data were also used in a multiple linear regression (MLR) model to relate these features to improvements in motor function as measured by the UPDRS Motor III scale.

The variability analysis results are consistent with the results we previously published describing the results from voluntary (single) and assisted (tandem) cycling by riders with PD [2].

III. Variability and Statistical Analysis methods

The following section describes the methods used for variability assessment and statistical analysis of captured rider data.

A. Approximate Entropy and Sample Entropy

Approximate entropy (ApEn) is a technique used to quantify the amount of regularity or unpredictability of fluctuations in time series data. Consider a time series of N instantaneous heart rate measurements $HR(1), HR(2), \dots, HR(N)$, and a time delay $\tau = 1$. Computation of

ApEn requires selecting two input parameters, m (pattern length) and r (criterion of similarity), where two patterns are *similar* if:

$$|HR(i+k) - HR(j+k)| < r \text{ for } 0 \leq k < m \quad (1)$$

Let P_m denote all patterns of length m for a given time series of length N . Define $C_{im}(r)$ as:

$$C_{im}(r) = \frac{n_{im}(r)}{N - m + 1} \quad (2)$$

where $n_{im}(r)$ is the number of patterns in P_m that are similar to the patterns of the same length that begins at i and $C_{im}(r)$ is the fraction of patterns of these similar length m patterns. We refer to $C_m(r)$ as the mean of $C_{im}(r)$ values which is a measure of the prevalence of repetitive patterns of length m in the time series. The ApEn for patterns of length m and similarity criterion r , is defined as:

$$\text{ApEn}(S_N, m, r) = \ln \left[\frac{C_m(r)}{C_{m+1}(r)} \right] \quad (3)$$

ApEn estimates the logarithmic likelihood that the next interval after each of the patterns will be different. For more details about the algorithm for computing ApEn refer to [8, 9].

Sample entropy (SaEn) is a modification of ApEn that removes the potential bias in ApEn by eliminating self-matches in the computation, which also reduces computational complexity. It also has the additional benefit that it can be applied to short time series data.

B. Spectral Entropy

Spectral entropy (SpEn) is a variability measure used to quantify the complexity of time series data in the frequency domain. SpEn is used to quantify frequency domain variability in power by computing the power-spectral-density (PSD) of the time series. The PSD is then normalized to produce a probability-like density function and then transformed with the Shannon function as follows.

1. Compute the Power Spectral Density (PSD) of the signal, $P(f)$.
2. Normalize the power spectrum:

$$Q(f) = \frac{P(f)}{\sum P(f)} \quad (4)$$

3. Compute the Shannon function:

$$H(f)=Q(f)\log\left(\frac{1}{Q(f)}\right) \quad (5)$$

4. Compute the Spectral Entropy (*SpEn*):

$$\text{Spec En} = \sum \frac{H(f)}{\log(N)} \quad (6)$$

Where N is the number of data points.

C. Multiple Regression Model

Statistical analysis, including multiple linear regression (MLR), logistic regression and computation of the odds ratio, was used to investigate the relationship between the measures of exercise variability and the related change in motor performance as measured by UPDRS Motor III scores.

The MLR model is defined as:

$$y_i = b_0 + b_1 x_{i,1} + b_2 x_{i,2} + \dots + b_k x_{i,k} + e_i, i=1, 2, \dots, n \quad (7)$$

where:

n : Number of observations (47)

k : Total number of predictors (6)

b_0 : Regression constant

b_k : Coefficient of the k^{th} predictor

$x_{i,k}$: Value of the k^{th} predictor in observation i

y_i : Predictand number i

e_i : Error term

The model parameters are estimated using the least squares method, although other methods can also be used. The resulting prediction equation is:

$$y_i = \hat{b}_0 + \hat{b}_1 x_{i,1} + \hat{b}_2 x_{i,2} + \dots + \hat{b}_k x_{i,k} \quad (8)$$

Where, “ $\wedge$ ” denotes estimated parameter values, and the regression residuals are defined as:

$$\hat{e}_i = y_i - \hat{y}_i \quad (9)$$

D. Logistic Regression and Odds Ratio

Logistic regression is used to predict the probability of occurrence of an event (odds) by fitting data to a logistic curve that relates the independent variable X to the rolling mean of the dependent variable $P(Y)$, using the following formula:

$$P = \frac{e^{a+bX}}{1+e^{a+bX}} \quad \text{or} \quad P = \frac{1}{1+e^{-(a+bX)}} \quad (10)$$

P is the probability of an event occurrence (the proportion of 1s, or the mean of Y), e is the base of the natural logarithm, and a and b are the model parameters.

The *odds ratio* is the ratio of the odds of an event occurring in one group to the odds of it occurring in another group. It is also used to refer to sample-based estimates of this ratio.

IV. Data Analysis Results

UPDRS Motor III assessment shows a significant difference between the static and dynamic groups (Table III). The average of UPDRS change in the static group is +0.4 (1.6 % worsening) compared to the dynamic group with an average UPDRS change of -4.21 (13.85 % improvement). There were slight differences in heart rate and power signals between the two groups (Table II). However, the pedaling cadence showed a significant difference ($F_{1,8} = 17.8$, $PCadence < 0.0001$) between the raw values in the static and dynamic groups. Cadence for the dynamic group (78.3 ± 3.2 RPM) was higher than the static group (68.3 ± 3.2 RPM) with less variability as quantified by the standard deviation. Power for the dynamic group (8.3 ± 4.3 W) was lower than the static group (31.7 ± 4.1 W).

Variability analysis reveals the hidden differences in signals between the two groups (Table IV). Comparison of each variable shows clear differences. Sample entropy (SaEn) for the cadence in the dynamic group (1.13) is significantly greater and different ($F_{1,8} = 22.2$, $P = 0.063$) than the SaEn for the cadence signal in the static group (0.42). This suggests that the cadence signals in the dynamic group have greater variability (less predictable) than the cadence signals in static group. The results for the power signal are opposite; that is, the power signals for the dynamic group (SaEn=0.22) show less variability (more predictable) and are significantly different ($F_{1,8} = 35.05$, $P = 0.0001$) from the power signals of the static group (SaEn=0.45).

Only the Spectral Entropies (SpEn) of the power signals are distinguishable between the static and dynamic groups. SpEn of the power in the dynamic group (0.2) showed significant variability ($F_{1,8} = 4.48$, $P < 0.0001$) as compared to the static group (0.10).

The data in Table III and Table IV have been used to develop a multiple linear regression model (MLR) and to compute the odds ratio for achieving the change in the UPDRS Motor

III scores in each group using logistic regression. Based on the distinguishable parameters in Table III and Table IV we selected six independent variables for the MLR model. The selected parameters are: Mean, StDv, and SaEn of cadence, and Mean, SaEn, and SaEn of power. The dependent variable of the MLR model is the change in UPDRS score. The MLR model development has been done in two ways: first two separate MLR models were built, one model for the static group (Table V) and one model for the dynamic group (Table VI), and then the data were combined into a single dataset, and another MLR model was built (Table VII). The residual values and the predicted UPDRS scores in Tables V and VI were obtained from MLR modeling using the “LinearModel” function in MATLAB. Two different models were built for each group of data: linear MLR model (model 1), and linear MLR with interactions (model 2). Figs. 3-4 show the correlation between the real and predicted UPDRS changes for three MLR models (static group, dynamic group, and combined static and dynamic groups). The linear model shows a small correlation between the real and predicted data for all three cases (Fig. 3). However, the linear model with interactions shows positive and significant correlation between real and predicted UPDRS change (Fig. 4).

Tables V, VI and VII contain the values of logistic regression and odds ratio computations for the two groups with different models. Here, the logistic regression shows the probability of improvement in motor function as quantified by a negative change in UPDRS score. The higher values of logistic regression and odds ratio for the dynamic group in each of the tables shows that the MLR model predicts a greater UPDRS improvement in the dynamic group, which is consistent with the real UPDRS data from the study.

V. Conclusions

In this study, the Smart Exercise Bike designed for rehabilitation in Parkinson's disease, and presented in [1], and [4] have been tested and validated in a clinical study with forty-seven PD patients, investigating the impact of cycling on changes in motor skills for riders with Parkinson's disease. The programmable controller on each bike enables two modes of exercise: static and dynamic cycling. In the static mode, the motor was operated with feedback control in order to maintain an active set point torque and the rider controlled the pedaling speed (cadence) of the bike. In the dynamic mode, the motor held a set point power value while a specified speed set point (80 RPM) was maintained and motor torque was adjusted to accommodate changes in force exerted by the rider on the pedals. Individuals who completed three sessions of dynamic cycling showed a 13.8% improvement in the Unified Parkinson's Disease Rating Scale (UPDRS), while individuals in the static group worsened by 1.6%. Comparing these results to previous studies [2, 3] shows that the dynamic control mode plays a role similar to tandem cycling used in previous PD bike exercise studies.

The variability analysis study reveals that pattern irregularity in power is greater in the static group compared to the dynamic group, indicating that the bike might provide a stable influence on the patient's exercise intensity, while maintaining elevated cadence in the dynamic mode, which is believed to be of significant value from previous studies [2, 3]. In contrast, the cadence data shows greater variability for the dynamic group than for the static

group. This variability is likely due to the inability of individuals with PD to maintain a constant high-speed pedal cadence. Furthermore, variability was also introduced when the bike in dynamic mode was required to increase or decrease pedal speed to maintain the desired cadence. The PD patients rode the bike in static mode at a self-selected cadence and thus showed lower variability during exercise bouts.

The observed variability in the sampled signals is likely not an artifact introduced by the specific control algorithm used, but is primarily due to the rider's performance in interacting with a bike under different speeds and loads. This is substantiated by the correlation between signal variability and motor skill changes for PD riders from a tandem bike study (no controller used) [2]. Furthermore, the linear regression model results, presented previously, show a positive correlation between the variability in cadence with improvement in motor skill performance. This suggests a causal link with variability and motor skill performance rather than an anomaly introduced by the specific control algorithm used.

The statistical analysis supports our previous results on tandem cycling [2] which identified that temporal variability or lack of predictability (not quantified by conventional statistical parameters such as variance or coefficient of variation) in cadence in dynamic mode (assisted exercise) can be used to predict resulting improvements in UPDRS Motor III scores. Lastly, using the MLR model, the predicted UPDRS Motor III scores are highly correlated to measured UPDRS values for test subjects in the dynamic group. These data provide insight into how time-series analysis methods can be applied to uncover potential features in the measured variables and how this information can be used to correlate exercise parameters with improved motor function.

Future Work and Consequences to Development of Rehabilitation Paradigms

This research has identified critical elements in high-intensity (active-assisted) exercise that may predict improved motor function in riders diagnosed with Parkinson's disease. However, there exists variability in each individual's response to exercise and the mechanism causing improvement is not well understood. Future work will focus on the development of patient-specific algorithms and methods that can adapt to changing patient conditions during a given exercise session as well as across multiple exercise sessions. Future studies will also examine the role of proprioceptive input during a bout of high cadence cycling on alterations of motor function using neuroimaging techniques.

Acknowledgments

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Nomenclature

UPDRS	Unified Parkinson's Disease Rating Scale
Stdev	standard deviation
ApEn	approximate entropy
SpEn	spectral entropy
SampEn	Sample entropy
RPM	revolutions per minute

Biographies

Hassan Mohammadi Abdar (S'12) received his B.S. degree in electronic engineering, his M.S. degree in control engineering from K. N. Toosi University of Technology, Tehran, Iran,

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Angela L. Ridgel (M'14) is an Associate Professor in Exercise Science/Physiology at Kent State University. She received her undergraduate degree in Biology from The College of William and Mary in Virginia, a Master's degree in Biology at Villanova University in Pennsylvania and her Doctoral degree in Biomedical Sciences from Marshall University in West Virginia. Dr. Ridgel completed her Post-Doctoral training at Case Western Reserve University and Cleveland Clinic. Dr. Ridgel's current research interests examine how exercise can be used for neurorehabilitation in individuals with Parkinson's disease and Multiple Sclerosis.

Fred M. Discenzo received two B.S. degrees in mathematics, the M.S. degree in polymer physics, and the Ph.D. degree in systems and control engineering from Case Western Reserve University, Cleveland, OH, USA. He is the Manager of Rockwell Automation's Advanced Technology Laboratory, Cleveland, OH, USA, and is a Rockwell Automation Fellow. He currently holds over 60 U.S. patents and has published many papers spanning artificial intelligence, machinery diagnostics, sensors, control, power scavenging, and artificial neural networks. Dr. Discenzo represents Rockwell Automation on various university/industry advisory committees, he serves on multiple conference committees, and is a board member of the Machinery Failure Prevention Technology (MFPT) Society.

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Kenneth A. Loparo (F'99) is the Nord Professor of Engineering in the Case School of Engineering, Case Western Reserve University, Cleveland, OH, USA. He has academic appointments in the Departments of Biomedical Engineering, Electrical Engineering and Computer Science, and Mechanical and Aerospace Engineering. His research interests include stability and control of nonlinear and stochastic systems; nonlinear filtering with applications to monitoring, fault detection, diagnosis and reconfigurable control; information theory aspects of stochastic and quantized systems with applications to adaptive and dual

control; the design of digital control systems; and advanced signal processing techniques for monitoring and tracking of physiological behavior.

Fig. 1.
Duplicating the tandem cycling with Smart Exercise Bike.

Fig. 2.
Smart exercise bike, completed system.

Fig. 3.

Correlation analysis of real (measured) versus predicted UPDRS values for linear MLR model. A: Static group (voluntary exercise). B: Dynamic group (active assisted exercise). C: Combined static and dynamic data. There was a positive, but small correlation of the real and predicted UPDRS Motor III scores in both the static ($r=0.39$) and dynamic ($r=0.30$) groups. Combined scores also maintained a positive, but not significant correlation ($r=0.39$) between real and predicted scores.

Fig. 4.

Correlation analysis of real (measured) versus predicted UPDRS values for linear model with interactions. A: Static group (voluntary exercise). B: Dynamic group (active-assisted exercise). C: Combined static and dynamic data. There was a positive and significant correlation between real and predicted UPDRS Motor III scores in both the static ($r=0.81$) and dynamic groups ($r=0.87$). Combined scores also maintained a positive and significant correlation between real and predicted scores ($r=0.63$).

Table I
Subject Demographics

	Static (n=23)	Dynamic (n=24)	p-value
Age (years)	67.26 ± 0.97	67.17 ± 1.66	0.962
Hoehn and Yahr Scale	1.83 ± 0.14	2.13 ± 0.16	0.151
Height (inch)	67.71 ± 0.74	68.15 ± 0.76	0.681
Weight (lbs)	165.17 ± 6.0	175.08 ± 8.14	0.336
BMI	25.08 ± 0.71	26.64 ± 0.91	0.186
PD duration (months)	77.74 ± 9.73	83.46 ± 11.17	0.702
Levodopa Equivalent Dose	153.32 ± 23.9	178.80 ± 29.4	0.507

Table II**Exercise Parameters**

	Static (n=23)	Dynamic (n=24)	p-value
Cadence (rpm)	68.3 ± 3.2	78.3 ± 1.1	0.000
Power (watts)	31.7 ± 4.1	8.3 ± 4.3	0.000
Heart Rate (bpm)	104.5 ± 3.1	95.3 ± 2.6	0.004
RPE (6-20 scale)	13.65 ± 0.40	12.71 ± 1.06	0.417

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Table III

Mean and variance for power, heart rate and cadence signals

Patient ID	Gender	Age	Group	UPDRS			Heart rate			Power			Cadence		
				Pre	Post	Change ^a	Mean ^b	Stdv		Mean ^b	Stdv		Mean ^b	Stdv	
SMB01	Male	68	Static	27	29	2	*	*		15.5	4.77		51.9	6.42	
SMB02	Male	68	Static	28	28	0	*	*		10.7	2.16		73.1	9.45	
SMB03	Female	75	Static	29	41	12	*	*		16.0	2.54		66.4	5.19	
SMB04	Male	73	Static	30	30	0	121.3	9.6		17.3	4.17		60.1	7.11	
SMB06	Male	61	Static	17	22	5	130.3	7.7		61.6	11.53		77.5	4.16	
SMB07	Female	68	Static	28	36	8	87.4	4.7		18.5	4.08		74.4	6.38	
SMB09	Male	69	Static	26	21	-5	105.4	22.3		31.5	5.75		80.3	4.57	
SMB10	Male	72	Static	41	30	-11	*	*		27.6	4.80		69.9	6.06	
SMB12	Female	67	Static	14	18	4	123.6	9.9		25.0	2.93		79.1	4.94	
SMB13	Male	76	Static	38	35	-3	*	*		7.70	2.56		50.6	6.29	
SMB17	Male	66	Static	18	26	8	60.0	0.0		48.0	10.40		81.1	4.41	
SMB20	Male	65	Static	18	20	2	93.6	4.7		39.9	13.21		65.2	6.99	
SMB25	Male	67	Static	35	38	3	98.3	6.8		42.5	8.60		80.6	3.89	
SMB26	Male	69	Static	41	45	4	90.7	4.8		30.7	6.50		43.9	7.03	
SMB28	Female	63	Static	24	19	-5	119.2	6.4		22.1	6.92		70.0	10.4	
SMB29	Male	65	Static	14	17	3	84.7	2.7		42.5	8.18		48.6	7.38	
SMB31	Female	61	Static	27	22	-5	132.6	7.4		19.6	3.73		69.2	5.43	
SMB34	Male	73	Static	27	24	-3	88.1	2.1		10.2	4.13		43.8	9.86	
SMB35	Female	67	Static	16	20	4	92.2	1.8		43.1	12.74		72.1	8.36	
SMB36	Male	71	Static	34	25	-9	112.7	9.9		48.5	9.53		78.4	6.32	
SMB38	Male	61	Static	22	22	0	102.0	5.9		45.2	9.38		73.0	5.61	
SMB40	Male	60	Static	11	5	-6	110.7	8.8		70.4	14.85		82.7	3.45	
SMB43	Female	62	Static	15	16	1	128.5	5.9		34.2	3.66		79.8	3.96	
MEAN		67.26		25.2	25.6	+0.4	104.5	6.7		31.7	6.83		68.3	6.2	
SMB05	Female	74	Dynamic	15	21	6	89.0	1.2		18.1	10.46		81.4	1.41	
SMB08	Male	75	Dynamic	24	27	3	119.0	21.3		20.1	9.05		79	3.73	
SMB11	Female	60	Dynamic	47	36	-11	*	*		-17.7	9.73		72	2.89	

Patient ID	Gender	Age	Group	UPDRS			Heart rate		Power		Cadence	
				Pre	Post	Change ^a	Mean ^b	Stdv	Mean ^b	Stdv	Mean ^b	Stdv
SMB14	Male	66	Dynamic	22	18	-4	112.4	12.1	54.1	10.02	88.1	1.47
SMB15	Male	74	Dynamic	35	43	8	80.1	2.6	-10.2	8.05	74.8	2.58
SMB16	Female	57	Dynamic	37	22	-15	115.8	7.1	26.1	9.51	84.6	1.97
SMB18	Male	63	Dynamic	20	11	-9	83.8	5.8	23.4	18.44	80.6	1.82
SMB19	Female	69	Dynamic	54	57	3	91.1	3.4	-16.1	7.23	71.6	6.38
SMB21	Male	53	Dynamic	30	28	-2	88.5	3.8	30.8	9.34	82.3	3.18
SMB22	Male	56	Dynamic	14	9	-5	105.5	16.5	45.7	13.42	84.6	1.41
SMB23	Female	78	Dynamic	35	36	1	80.3	1.9	-14.6	6.97	73.4	2.05
SMB24	Male	62	Dynamic	23	15	-8	89.7	3.1	20.0	10.45	81.6	1.86
SMB27	Male	60	Dynamic	18	9	-9	90.4	3.1	24.3	14.13	81.7	1.42
SMB30	Male	60	Dynamic	19	19	0	108.2	3.9	4.10	14.15	78.6	3.59
SMB32	Female	78	Dynamic	48	44	-4	84.2	1.3	-17.50	4.70	71.3	1.98
SMB33	Female	78	Dynamic	29	29	0	94.6	1.3	0.40	6.95	78.8	1.15
SMB37	Female	57	Dynamic	27	20	-7	71.7	2.9	-6.90	5.50	76.6	1.38
SMB39	Female	73	Dynamic	34	34	0	110.4	20.0	26.30	6.47	79.8	4.57
SMB41	Female	72	Dynamic	22	16	-6	100.1	4.8	8.00	10.96	78.9	4.30
SMB42	Female	75	Dynamic	21	15	-6	86.5	3.6	3.00	8.77	79.1	1.43
SMB44	Male	76	Dynamic	52	27	-25	96.4	4.2	-6.80	14.69	72.3	5.51
SMB45	Male	72	Dynamic	55	47	-8	73.3	1.93	-24.50	6.65	72.9	4.28
SMB46	Female	60	Dynamic	4	1	-3	111.3	21.04	-9.20	7.98	75.1	4.51
SMB47	Male	64	Dynamic	45	45	0	110.4	2.86	18.10	6.28	79.8	1.82
MEAN		67.16		30.4	26.2	-4.21	95.3	6.52	830	9.58	78.3	2.8

^aNegative change in UPDRS represents improvements in motor function

^bMean values were calculated over 3 exercise sessions per patient

*Due to heart rate sensor failure, data was inaccurate

Table IV
Mean of ApEn and SpEn for power, heart rate and cadence signals over three sessions

Patient ID	Group	UPDRS Change	Heart Rate			Power			Cadence		
			SaEn	SpEn	SpEn	SaEn	SpEn	SpEn	SaEn	SpEn	SpEn
SMB01	Static	2	*	*	*	0.51	0.09	0.33	0.08	0.08	0.08
SMB02	Static	0	*	*	*	0.72	0.08	0.04	0.04	0.08	0.08
SMB03	Static	12	*	*	*	1.00	0.08	0.51	0.51	0.07	0.07
SMB04	Static	0	0.0	0.1	0.1	0.45	0.09	0.24	0.24	0.07	0.07
SMB06	Static	5	0.1	0.1	0.1	0.05	0.07	0.72	0.72	0.07	0.07
SMB07	Static	8	0.0	0.1	0.1	0.23	0.08	0.17	0.17	0.07	0.07
SMB09	Static	-5	0.0	0.1	0.1	0.29	0.07	0.54	0.54	0.07	0.07
SMB10	Static	-11	*	*	*	0.54	0.08	0.49	0.49	0.07	0.07
SMB12	Static	4	0.08	0.07	0.07	1.00	0.08	0.58	0.58	0.07	0.07
SMB13	Static	-3	1.15	0.07	0.07	0.89	0.10	0.38	0.38	0.08	0.08
SMB17	Static	8	*	*	*	0.08	0.07	0.59	0.59	0.07	0.07
SMB20	Static	2	0.18	0.07	0.07	0.07	0.09	0.29	0.29	0.07	0.07
SMB25	Static	3	0.02	0.07	0.12	0.12	0.07	0.74	0.74	0.07	0.07
SMB26	Static	4	0.62	0.07	0.96	0.96	0.15	0.43	0.43	0.10	0.10
SMB28	Static	-5	0.05	0.07	0.12	0.12	0.08	0.10	0.10	0.07	0.07
SMB29	Static	3	0.35	0.07	0.86	0.86	0.15	0.26	0.26	0.11	0.11
SMB31	Static	-5	0.02	0.07	0.67	0.67	0.08	0.54	0.54	0.07	0.07
SMB34	Static	-3	0.95	0.07	0.64	0.64	0.13	0.14	0.14	0.10	0.10
SMB35	Static	4	0.01	0.07	0.26	0.26	0.08	0.13	0.13	0.07	0.07
SMB36	Static	-9	0.01	0.07	0.06	0.06	0.08	0.29	0.29	0.07	0.07
SMB38	Static	0	0.11	0.07	0.08	0.08	0.08	0.40	0.40	0.07	0.07
SMB40	Static	-6	0.03	0.07	0.02	0.02	0.07	0.81	0.81	0.07	0.07
SMB43	Static	1	0.02	0.07	0.71	0.71	0.07	0.73	0.73	0.07	0.07
MEAN		+0.4	0.21	0.07	0.45	0.45	0.09	0.42	0.42	0.08	0.08
SMB05	Dynamic	6	0.78	0.07	0.14	0.14	0.28	1.55	1.55	0.07	0.07
SMB08	Dynamic	3	0.01	0.07	0.07	0.07	0.31	0.66	0.66	0.07	0.07
SMB11	Dynamic	-11	*	*	*	0.09	0.13	0.66	0.66	0.07	0.07

Patient ID	Group	UPDRS Change	Heart Rate		Power		Cadence	
			SaEn	SpEn	SaEn	SpEn	SaEn	SpEn
SMB14	Dynamic	-4	0.51	0.07	0.11	0.09	1.40	0.07
SMB15	Dynamic	8	0.66	0.07	0.24	0.18	0.96	0.07
SMB16	Dynamic	-15	0.02	0.07	0.22	0.17	1.02	0.07
SMB18	Dynamic	-9	0.57	0.07	0.10	0.32	1.38	0.07
SMB19	Dynamic	3	0.94	0.07	0.31	0.12	0.99	0.07
SMB21	Dynamic	-2	0.26	0.07	0.17	0.12	1.09	0.07
SMB22	Dynamic	-5	0.04	0.07	0.03	0.10	1.08	0.07
SMB23	Dynamic	1	1.21	0.07	0.33	0.12	1.20	0.07
SMB24	Dynamic	-8	0.58	0.07	0.12	0.26	1.16	0.07
SMB27	Dynamic	-9	0.44	0.07	0.06	0.21	1.33	0.07
SMB30	Dynamic	0	0.10	0.07	0.07	0.36	0.60	0.07
SMB32	Dynamic	-4	1.01	0.07	0.52	0.08	1.13	0.07
SMB33	Dynamic	0	0.58	0.07	0.34	0.29	1.92	0.07
SMB37	Dynamic	-7	0.38	0.07	0.39	0.13	1.32	0.07
SMB39	Dynamic	0	0.38	0.07	0.34	0.12	0.86	0.07
SMB41	Dynamic	-6	0.08	0.07	0.10	0.42	0.63	0.07
SMB42	Dynamic	-6	0.86	0.07	0.19	0.28	1.55	0.07
SMB44	Dynamic	-25	0.07	0.07	0.24	0.11	1.08	0.07
SMB45	Dynamic	-8	1.10	0.07	0.22	0.08	0.92	0.07
SMB46	Dynamic	-3	0.20	0.07	0.33	0.08	1.14	0.07
SMB47	Dynamic	0	0.50	0.07	0.57	0.34	1.52	0.07
MEAN		-4.21	0.49	0.07	0.22	0.20	1.13	0.07

* Due to heart rate sensor failure, data was inaccurate

Table V

Regression analysis results for the static group

Patient ID	Real	UPDRS Change		Residuals		P (Logistic ratio)		Odds Ratio (P/(1-P))	
		Predicted		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
		Model 1	Model 2						
SMB01	2	1.3	0.4	0.7	1.6	0.22	0.40	0.3	0.7
SMB02	0	-0.2	0.3	0.2	-0.3	0.55	0.42	1.2	0.7
SMB03	12	3.2	11.2	8.8	0.8	0.04	0.00	0.0	0.0
SMB04	0	0.9	1.9	-0.9	-1.9	0.28	0.13	0.4	0.1
SMB06	5	-0.9	3.4	5.9	1.6	0.71	0.03	2.5	0.0
SMB07	8	2.6	5.9	5.4	2.1	0.07	0.00	0.1	0.0
SMB09	-5	0.8	2.4	-5.8	-7.4	0.31	0.09	0.5	0.1
SMB10	-11	-0.5	-10.1	-10.5	-0.9	0.63	1.00	1.7	23349.0
SMB12	4	2.7	2.4	1.3	1.6	0.06	0.08	0.1	0.1
SMB13	-3	2.2	-2.4	-5.2	-0.6	0.10	0.92	0.1	11.5
SMB17	8	0.2	-3.7	7.8	11.7	0.46	0.98	0.9	42.0
SMB20	2	-0.5	2.3	2.5	-0.3	0.62	0.09	1.6	0.1
SMB25	3	-1.7	3.7	4.7	-0.7	0.85	0.02	5.7	0.0
SMB26	4	1.1	4.2	2.9	-0.2	0.24	0.01	0.3	0.0
SMB28	-5	-6.4	-5.4	1.4	0.4	1.00	1.00	593.6	232.1
SMB29	3	3.8	2.9	-0.8	0.1	0.02	0.05	0.0	0.1
SMB31	-5	0.2	-5.0	-5.2	0.0	0.44	0.99	0.8	152.5
SMB34	-3	-3.3	-3.1	0.3	0.1	0.96	0.96	26.1	22.5
SMB35	4	0.5	2.7	3.5	1.3	0.38	0.06	0.6	0.1
SMB36	-9	1.4	-5.0	-10.4	-4.0	0.19	0.99	0.2	150.4
SMB38	0	1.0	1.3	-1.0	-1.3	0.26	0.21	0.4	0.3
SMB40	-6	-0.6	-2.7	-5.4	-3.3	0.65	0.94	1.9	14.9
SMB43	1	1.1	1.5	-0.1	-0.5	0.25	0.18	0.3	0.2

Table VI

Regression analysis results for the dynamic group

Patient ID	Real	UPDRS Change		Residuals		P (Logistic ratio)		Odds Ratio (P/(1-P))	
		Predicted		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
		Model 1	Model 2						
SMB05	6	-4.1	-5.1	10.1	11.1	0.98	0.99	61.3	167.3
SMB08	3	-3.4	1.2	6.4	1.8	0.97	0.23	29.2	0.3
SMB11	-11	-6.3	-10.7	-4.7	-0.3	1.00	1.00	571.0	44287.0
SMB14	-4	-6.5	-2.7	2.5	-1.3	1.00	0.94	674.9	14.7
SMB15	8	-4.1	9.2	12.1	-1.2	0.98	0.00	59.5	0.0
SMB16	-15	-3.9	-15.6	-11.1	0.6	0.98	1.00	47.7	6.11E+6
SMB18	-9	-3.6	-6.8	-5.4	-2.2	0.97	1.00	35.1	887.4
SMB19	3	-6.0	0.2	9.0	2.8	1.00	0.46	402.4	0.8
SMB21	-2	-5.7	-5.1	3.7	3.1	1.00	0.99	304.7	169.7
SMB22	-5	-6.6	-6.4	1.6	1.4	1.00	1.00	772.5	580.5
SMB23	1	-4.2	-4.7	5.2	5.7	0.99	0.99	67.0	109.3
SMB24	-8	-4.0	-3.1	-4.0	-4.9	0.98	0.96	53.1	22.1
SMB27	-9	-5.6	-3.8	-3.4	-5.2	1.00	0.98	267.8	43.3
SMB30	0	-2.9	-2.9	2.9	2.9	0.95	0.95	18.1	18.4
SMB32	-4	-2.1	-2.5	-1.9	-1.5	0.89	0.92	8.2	12.2
SMB33	0	-2.5	2.4	2.5	-2.4	0.92	0.08	11.9	0.1
SMB37	-7	-3.2	-6.6	-3.8	-0.4	0.96	1.00	24.5	726.3
SMB39	0	-3.6	1.5	3.6	-1.5	0.97	0.18	36.7	0.2
SMB41	-6	-1.8	-3.3	-4.2	-2.7	0.86	0.97	6.3	28.5
SMB42	-6	-3.8	-4.5	-2.2	-1.5	0.98	0.99	45.4	94.3
SMB44	-25	-6.6	-22.7	-18.4	-2.3	1.00	1.00	725.4	7.14E+9
SMB45	-8	-7.0	-6.3	-1.0	-1.7	1.00	1.00	1131.7	518.9
SMB46	-3	-5.9	-2.4	2.9	-0.6	1.00	0.91	347.7	10.5
SMB47	0	2.5	-0.4	-2.5	0.4	0.08	0.59	0.1	1.4

Table VII
Combined static and dynamic group data regression analysis results

Patient ID	Real	UPDRS Change		Residuals		P (Logistic ratio)		Odds Ratio (P/(1-P))	
		Predicted		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
		Model 1	Model 2						
SMB01	2	-0.2	-0.4	2.2	2.4	0.54	0.60	1.2	1.5
SMB02	0	0.5	2.1	-0.5	-2.1	0.37	0.11	0.6	0.1
SMB03	12	3.0	5.1	9.0	6.9	0.05	0.01	0.1	0.0
SMB04	0	-0.5	-0.3	0.5	0.3	0.63	0.57	1.7	1.3
SMB06	5	-1.4	-0.4	6.4	5.4	0.80	0.60	4.0	1.5
SMB07	8	-1.3	6.0	9.3	2.0	0.78	0.00	3.6	0.0
SMB09	-5	-0.8	0.7	-4.2	-5.7	0.70	0.34	2.3	0.5
SMB10	-11	0.1	-5.9	-11.1	-5.1	0.47	1.00	0.9	376.4
SMB12	4	3.3	5.3	0.7	-1.3	0.03	0.00	0.0	0.0
SMB13	-3	1.9	0.7	-4.9	-3.7	0.13	0.33	0.2	0.5
SMB17	8	-1.5	-0.9	9.5	8.9	0.82	0.71	4.4	2.5
SMB20	2	-2.0	4.5	4.0	-2.5	0.88	0.01	7.5	0.0
SMB25	3	-1.9	-2.1	4.9	5.1	0.87	0.89	6.7	8.0
SMB26	4	3.4	1.9	0.6	2.1	0.03	0.13	0.0	0.1
SMB28	-5	-3.8	-3.9	-1.2	-1.1	0.98	0.98	46.8	48.7
SMB29	3	3.9	6.1	-0.9	-3.1	0.02	0.00	0.0	0.0
SMB31	-5	0.7	-0.8	-5.7	-4.2	0.33	0.69	0.5	2.2
SMB34	-3	-0.4	-4.0	-2.6	1.0	0.60	0.98	1.5	56.6
SMB35	4	-0.6	-6.3	4.6	10.3	0.65	1.00	1.9	549.3
SMB36	-9	-1.3	0.5	-7.7	-9.5	0.78	0.38	3.6	0.6
SMB38	0	-1.4	1.9	1.4	-1.9	0.81	0.13	4.2	0.1
SMB40	-6	-1.1	0.0	-4.9	-6.0	0.75	0.51	3.0	1.0
SMB43	1	1.7	-1.2	-0.7	2.2	0.16	0.77	0.2	3.3
SMB05	6	-4.4	-5.7	10.4	11.7	0.99	1.00	78.9	313.1
SMB08	3	-1.8	-2.2	4.8	5.2	0.86	0.90	6.1	9.2

Patient ID	Real	UPDRS Change		Residuals		P (Logistic ratio)		Odds Ratio (P/(1-P))	
		Predicted		Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
		Model 1	Model 2						
SMB11	-11	-4.6	-6.6	-6.4	-4.4	0.99	1.00	95.4	711.8
SMB14	-4	-3.3	-2.4	-0.7	-1.6	0.96	0.92	26.1	11.4
SMB15	8	-3.9	2.1	11.9	5.9	0.98	0.11	51.7	0.1
SMB16	-15	-2.1	-8.2	-12.9	-6.8	0.89	1.00	7.8	3826.4
SMB18	-9	-3.5	-2.5	-5.5	-6.5	0.97	0.92	34.0	12.1
SMB19	3	-6.5	-4.5	9.5	7.5	1.00	0.99	698.6	88.8
SMB21	-2	-3.5	-4.5	1.5	2.5	0.97	0.99	33.4	86.9
SMB22	-5	-2.7	-6.5	-2.3	1.5	0.94	1.00	15.1	684.7
SMB23	1	-4.8	-7.6	5.8	8.6	0.99	1.00	119.9	1954.8
SMB24	-8	-3.0	-7.6	-5.0	-0.4	0.95	1.00	20.5	2089.8
SMB27	-9	-4.1	-8.9	-4.9	-0.1	0.98	1.00	58.5	7410.0
SMB30	0	-2.0	0.1	2.0	-0.1	0.88	0.49	7.3	0.9
SMB32	-4	-3.6	-0.7	-0.4	-3.3	0.97	0.68	35.4	2.1
SMB33	0	-5.4	1.8	5.4	-1.8	1.00	0.15	232.1	0.2
SMB37	-7	-4.0	-1.7	-3.0	-5.3	0.98	0.85	56.6	5.6
SMB39	0	-2.3	-1.4	2.3	1.4	0.91	0.80	10.4	3.9
SMB41	-6	-1.7	-3.8	-4.3	-2.2	0.84	0.98	5.4	43.9
SMB42	-6	-4.9	-1.7	-1.1	-4.3	0.99	0.84	131.2	5.3
SMB44	-25	-6.5	-11.3	-18.5	-13.7	1.00	1.00	659.6	84882.0
SMB45	-8	-6.4	-10.6	-1.6	2.6	1.00	1.00	593.3	40443.0
SMB46	-3	-5.9	-4.7	2.9	1.7	1.00	0.99	370.5	111.9
SMB47	0	-1.1	-1.3	1.1	1.3	0.75	0.79	3.0	3.8