Classification of Cycling Exercise Status Using Short-term Heart Rate Variability

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Abstract— **Introduction of effective home-based exercise programs in older adults and people with chronic conditions requires implementation of appropriate safeguards to prevent possible side effects of strenuous exercise. In each exercise program the following exercise modes can be generally recognized: rest, main exercise, and exercise recovery. However, approaches for automated identification of these exercise modes have not been studied systematically. The primary purpose of this study was (1) to assess whether time-domain HRV parameters differ depending on exercise mode; (2) to identify optimal set of time-domain parameters for automated classification of exercise mode and build a classification model. Using discriminant analysis, two HRV parameters (RRtri and MeanRR) were identified which yielded 80% classification success in identifying correct exercise mode by applying generated discriminant functions.**

I. Introduction

Telerehabilitation systems supporting home-based exercise are gaining wide recognition [1-3]. High acceptance of home-based physical telerehabilitation systems has been demonstrated in individuals with mobility impairments, frail elderly, and people with chronic cardiovascular conditions [4-6]. Introduction of effective home-based exercise programs in older adults and people with chronic conditions requires implementation of appropriate safeguards to prevent possible side effects of strenuous exercise. In each exercise program the following exercise modes can be generally recognized: rest, main exercise, and exercise recovery. However, approaches for automated identification of these exercise modes have not been studied systematically. The goal of this pilot project was to explore opportunities of automated classification of general exercise modes using heart rate variability (HRV) analysis.

Changes in autonomic control of heart rate during and after exercise have been previously described [7-8]. Most of the studies used HRV parameters in frequency domain to identify changes in autonomic control occurring over time during endurance training [9-10]. The limitation of using HRV in frequency domain is that these parameters are generally more applicable for a stable process and require longer periods for analysis. For intra-exercise monitoring shorter periods of analysis may be preferred with understanding that during exercise autonomic control is in transition. Analysis of short-term HRV parameters in time domain has been shown effective during transitional processes in autonomic balance caused by various types of stress [11-12]. These techniques for HRV analysis have not been applied systematically for intra-exercise monitoring of autonomic control.

The primary purpose of this study was (1) to assess whether time-domain HRV parameters differ depending on exercise mode; (2) to identify optimal set of time-domain parameters for automated classification of exercise mode and build a classification model.

II. Methods

A. System and Data Acquisition

Five consecutive healthy adult volunteers (2 females and 3 males) participated in the study. The participants were asked to use the interactive Biking Exercise (iBikE) system [13-14] for cycling exercise of two different intensities. They were guided by the iBikE system in following a standardized exercise procedure which consisted of the following five consecutive steps: (1) 1-min rest; (2) 5-min lower intensity exercise; (3) 1-min recovery; (4) 5-min higher intensity exercise; (5) 1-min recovery. For further analysis, the step #1 was called “Rest,” the steps #2 and #4 were called “Exercise,” and the steps #3 and #5 were called “Recovery.” In this study, both lower and higher intensity exercises consisted of lower limb cycling. The iBikE system presented exercise intensity on an interactive touch screen dashboard helping users in following their exercise prescription [15].

The first 5-min cycling exercise intensity was 1.5 miles/hour and the second 5-min cycling exercise intensity was 2.5 miles/hour. Overall, the exercise procedure took 13 minutes. Each participant made three study visits on different days within 1-2 weeks repeating the same 13-min exercise procedure during each study visit. Before starting the exercise procedure, a wireless electrocardiogram (ECG) sensor (BN-RSPE, BIOPAC Systems, Inc., USA) was mounted on participant chest. Pre-gelled/disposable ECG electrodes (LL Electrode Series, Lead-Lok®, Inc., USA) leads were connected to the participant to obtain a Lead II trace.

The actual 13-min exercise procedure (including 1-min rest at the beginning) commenced after 5-minute resting period to achieve cardiovascular system stabilization. During the exercise procedure, 1-kHz ECG was continuously sampled by a data acquisition system (MP150, Biopac Systems, Inc., USA) that was connected to a laptop. Raw data from ECG were band-limited from 0.05 Hz to 150 Hz to minimize noise.

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B. Analysis

Each 13-minute exercise procedure has been split into 13 consecutive 1- minute tracings of raw ECG signal consisting of 1 “Rest” tracing, 10 “Exercise” tracings, and 2 “Recovery” tracings. The tracings were obtained from each volunteer by data acquisition software (AcuKnowledges 4.2, BIOPAC Systems, Inc., USA). Since each of the 5 participants performed 3 times the standardized 13-min exercise procedure, the final analysis included 15 1-min “Rest” tracings, 150 1-min “Exercise” tracings, and 30 1-min “Recovery” tracings. Each 1-min ECG tracing was analyzed by a specialized HRV analysis software [16]. The resulting HRV analysis yielded the following time-domain parameters of HRV for each 1-min tracing: the mean of RR intervals (MeanRR), standard deviation of RR intervals (SDRR), square root of the mean squared difference between successive RR intervals (RMSSD), number of successive RR interval pairs that differ more than 50 ms (NN50), NN50 divided by the total number of RR intervals (pNN50), the integral of the RR interval histogram divided by the height of the histogram (RRtri), baseline width of the RR interval histogram (TINN). Each 1-min tracing was categorized as “Rest,” “Exercise” or “Recovery” and resulting HRV parameters were assigned to the corresponding category.

All statistical analyses were performed using IBM SPSS Statistics 21 (IBM, USA). Group statistics and bivariate correlation analyses were conducted to examine the overall means and standard deviations of the continuous 7 time-domain parameters of HRV for 3 exercise categories (“Rest,” “Exercise” or “Recovery”). Relationships between each HRV time-domain parameter were investigated by correlation analysis. Discriminant analysis was conducted (1) to find the best variable set for discrimination among 3 exercise modes; (2) to compose discriminant functions based on linear parameter combinations; and (3) to build a predictive model for automated identification of exercise mode using time-domain HRV parameters. To achieve that a stepwise analysis was carried out, specifically Wiks’ lambda method was used.

III. Results

A. Group statistics and Correlations

The means and standard deviations of 7 time-domain HRV parameters were calculated for each of 3 exercise modes as well as for total exercise procedure. As shown in TABLE I, all 7 HRV parameters changed significantly during transition from one exercise mode to another. Generally, HRV values of “Exercise” appeared to be lower than values of “Rest” and ‘Recovery’. Between HRV values of “Rest” and “Recovery,” no unidirectional changes were observed with specific change directions depending on a particular parameter. Bivariate correlations between each HRV time-domain parameter ranged from 0.070 to 0.990 as can be seen in TABLE II. For SDRR, correlation with the other parameters exceeded 50%. Other notable correlations exceeding 50 % were found between RMSSD and NN50, RMSSD and pNN50, RMSSD and TINN, NN50 and pNN50, NN50 and TINN, and pNN50 and TINN.

TABLE II. HRV Depemding on Exercise Mode

	Rest		**Exercise**		**Recovery**		**Total**	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
MeanRR	811.72	131.23	557.19	94.67	616.19	116.55	585.84	121.98
SDRR	32.70	14.63	25.84	25.91	59.24	26.87	31.51	27.98
RMSSD	20.85	8.04	18.56	31.30	28.36	39.92	20.25	31.75
NN50	2.60	5.91	1.76	6.00	2.83	4.09	1.99	5.73
pNN50	3.18	6.54	1.72	6.24	3.19	5.11	2.06	6.11
RRtri	6.71	1.85	4.23	2.20	9.19	3.16	5.18	2.97
TINN	143.33	94.58	114.80	118.37	232.83	138.86	135.15	126.85

SD: standard deviation, N are:
15 for **Rest**, 150 for **Exercise**, 30 for **Recovery**, and 195 for **Total**,
MeanRR (ms): the mean of RR intervals, SDRR (ms): standard deviation of RR intervals,
RMSSD (ms): squre root of the mean squared difference between successive RR intervals,
NN50 (n.u.): number of successive RR interval pairs that differ more than 50 ms,
pNN50 (%): NN50 divided by the total number of RR intervals,
RRtri (n.u.): the integral of the RR interval histogram divided by the height of the histogram,
TINN (ms): baseline width of the RR interval histogram

TABLE III. HRV Parameter Correlations

	MeanRR					
SDRR	0.203	SDRR				
RMSSD	0.071	0.798	RMSSD			
NN50	0.083	0.553	0.610	NN50		
pNN50	0.133	0.537	0.576	0.990	pNN50	
RRtri	0.488	0.593	0.202	0.318	0.345	RRtri
TINN	0.070	0.921	0.858	0.552	0.513	0.473

TABLE IV. Parameters in the Discriminant Analysis

Step		**Tolerance**	**F to Remove**		**Wilks' Lambda**	
1	RRtri	1.000	59.110			
2	RRtri	0.762	56.247	50.205	0.683	0.430
	MeanRR	0.762	42.086		0.619	

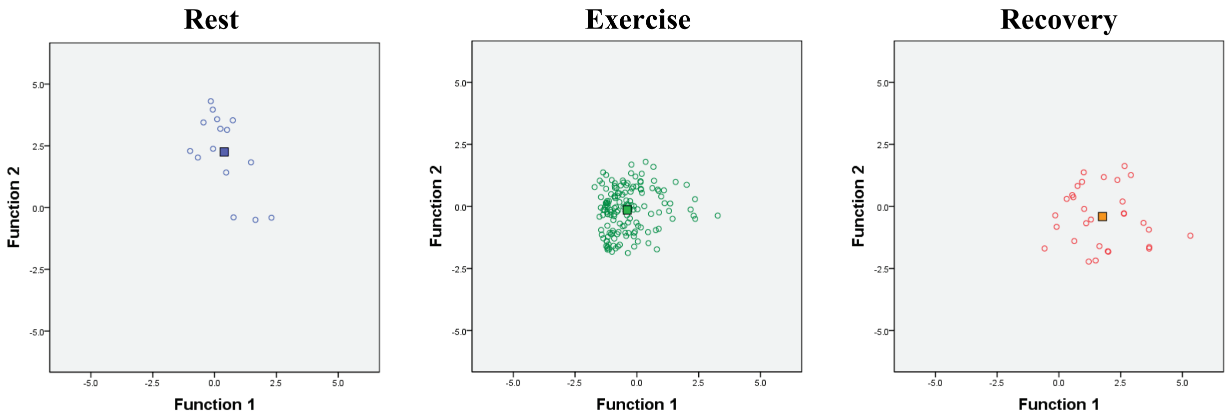
TABLE V. Eigenvalues in the Discriminant Analysis

Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**CC**
1	0.618	58.5	58.5	0.618
2	0.439	41.5	100.0	0.552

CC: canonical correlation

B. Canonical Discriminant Functions

To discriminate a priori defined categorical groups (“Rest,” “Exercise,” and “Recovery”), a stepwise discriminant analysis was performed. At each step, the parameters that minimized the overall Wilks’ Lambda were entered. The maximum number of steps was 14, entered time-domain parameters of HRV were RRtri and MeanRR, and the other 5 time-domain parameters of HRV were removed. In the resulting model, RRtri had 0.762 of tolerance, 56.472 of F to Remove and 0.683 of Wilks’ Labda, MeanRR had 0.762 of tolerance, 42.086 of F to Remove and 0.619 of Wilks’ Lambda, and the model made by RRtri and MeanRR had



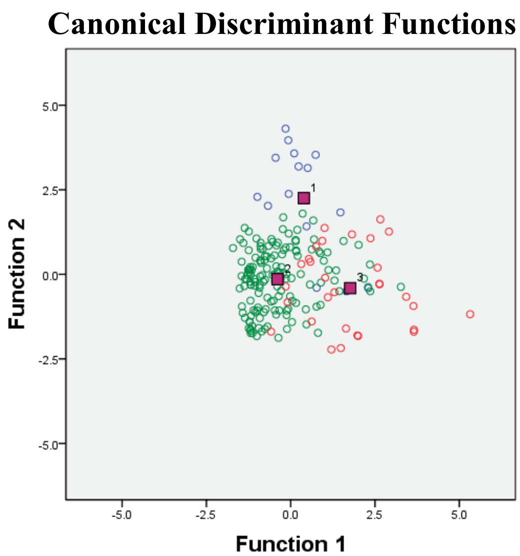


TABLE I. CLASSIFICATION RESULTS

		Modes	Predicted Group Membership			Total
			Rest	Exercise	Recovery	
Original	Count	Rest	12	0	3	15
		Exercise	8	123	19	150
		Recovery	3	6	21	30
	%	Rest	80.0	0.0	20.0	100.0
		Exercise	5.3	82.0	12.7	100.0
		Recovery	10.0	20.0	70.0	100.0
Cross-validated	Count	Rest	12	0	3	15
		Exercise	8	123	19	150
		Recovery	3	6	21	30
	%	Rest	80.0	0.0	20.0	100.0
		Exercise	5.3	82.0	12.7	100.0
		Recovery	10.0	20.0	70.0	100.0

Figure 1. Groups Graphs

50.205 of F to Remove and 0.430 of Wilks' Lambda as shown in TABLE III.

As the result of this analysis, two canonical linear discriminant functions were generated to calculate Score1 and Score 2:

$$\text{Score 1} = 0.45\ \text{RRtri} - 0.001\ \text{MeanRR} - 1.564$$

$$\text{Score 2} = -0.187\ \text{RRtri} + 0.011\ \text{MeanRR} - 5.612$$

The eigenvalues of Function 1 and 2 were 0.618 and 0.439 respectively. The proportion of discriminating abilities of the Function 1 and Function 2 were 58.5 % and 41.5 % respectively. The canonical correlations of Function 1 and Function 2 were 0.618 and 0.552 respectively as shown in TABLE IV.

C. *Classification Statistics*

The classification was processed for overall 195 sets that included 15 sets of "Rest," 150 sets of "Exercise," and 30 sets of "Recovery," and the prior probabilities was set for all groups equal.

As shown in Figure 1, the group centroids (Function 1, Function 2) of "Rest," "Exercise" and "Recovery" were (0.390, 2.252), (-0.392, -0.144) and (1.784, -0.408) respectively. The graph of all combined groups is also shown in Figure 1.

The classification results are shown in TABLE V. The classification success was assessed using original and cross-validated modes which in case of our data sets did not differ. Percentage of correct and incorrect classifications was based on the generated Function 1 and Function 2. In case of "Rest," 80% of observations were classified correctly as "Rest" group, but the remaining cases were incorrectly classified as "Recovery" (20%). In case of "Exercise," 82% of observations were correctly identified as "Exercise," but 5.3 % were misclassified as "Rest" and 12.7% - as "Recovery." In case of "Recovery," 70 % of observations were correctly classified as "Recovery" but 10 % were misidentified as "Rest" and 20% - as "Exercise." In cross-validation each case was classified by the functions derived from all cases using the leave-one-out method. As shown in TABLE V, there were no difference in prediction of the actual exercise mode between the original validation and the cross-validation. Both classification estimates yielded overall 80% of correctly classified cases using Function 1 and Function 2 generated by discriminant analysis.

IV. Discussion

In this study, we were able to demonstrate a possibility of automated classification of exercise mode using HRV time-domain parameters. Seven major HRV time-domain parameters were acquired during three exercise modes including "Rest," "Exercise" and "Recovery" to assess whether the HRV parameters are affected by the exercise modes and to identify the optimal combination of these parameters to discriminate between these 3 exercise modes. Statistical analyses clearly demonstrated effect of exercise mode on the HRV parameters and determined discriminant functions to classify the exercise modes. Three main findings from this study are discussed below.

First, the mean values of 7 continuous numeric time-domain parameters of HRV were obtained for each exercise mode. The group statistics showed that the mean values differ between 3 modes of exercise. The observed differences among 3 modes of exercise supported the assumption that these 7 numerical parameters can potentially be used to categorize exercise mode automatically as "Rest," "Exercise" and "Recovery." The correlations among 7 time-domain parameters of HRV demonstrated that there were potentially redundant parameters. High correlation between certain parameters showed that number of parameters may be reduced however low correlation between certain parameters underscored their potential unique contribution for the classification.

Second, discriminant analysis allowed identify optimal combination or predictive parameters. Using stepwise discriminant analysis with overall 7 initial predictive parameters for categorizing the modes of exercise we were able to reduce number of predictive parameters to two. Among these 7 HRV parameters, RRtri and MeanRR were found for the final parameters for the classification.

Third, Score1 and Score 2 were generated from two canonical linear discriminant functions, the territoral map was configured by Fisher's linear discriminant function coefficient, and each data point for "Rest," "Exercise" and "Recovery" modes was separated and described. In these graphs, the location of each data point is presented by (Score 1, Score 2) and the one-point that represented a characteristic of all data in each mode could be confirmed. The graph of canonical discriminant functions represented all data, their locations, and each mode's centroid. In this graph, the distances between two modes and the graphical degree of classification could be found. Some data overlapped adjacent regions, and then the data overlapped on the graph of canonical discriminant functions. Therefore, the overlapped data resulted in errors of classification that were 20 % of 'Rest', 18 % of 'Exercise' and 30 % of 'Recovery'. Thus, better classification results may be obtained by accounting not only for the exercise mode but also in which stage of the mode the subject is (beginning, middle, or end). This can be accomplished in future studies with inclusion of a larger sample. However, overall 80% classification agreement is very promising and warrants further investigation.

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