SNAPSHOT EVALUATION OF FATIGUE DURING SKIING EXERCISE

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Abstract—We have measured and analyzed the heart rate variability (HRV) and myoelectric (ME) signals during skiing exercise for a whole day. To realize snapshot evaluation of functional activities for this long-term exercise, we developed a radio controlled remote data acquisition system, and then evaluated data using spectrum analysis. Actually, we compared the spectrum of the HRV between skiing and ski lift riding, within the target frequency bands, using the Wavelet analysis. During skiing, we estimated the amplitude and frequency indices as ME parameters. Then we applied the principal component analysis and the ARX model to represent the changes in functional activities. The results quantitatively showed the time-varying features of dominant frequency components in HRV and the relationship between cardiovascular and muscular activities with the progression of fatigue.

I. INTRODUCTION

We are studying biosignal processing developed for snapshot evaluation of the relationship between the feeling of fatigue and the muscular fatigue during skiing exercise. For representing the feeling of fatigue at the central nervous system, we used the spectrum analysis of the heart rate variability (HRV). On the other hand, muscular fatigue has been studied by surface myoelectric (ME) signals.

The HRV is dynamically controlled under the autonomic nervous system and the frequency components are considered as the indices of the sympatho-vagal balance [1]. Clarys and colleagues [2] studied ergonomic analyses of downhill skiing and reported that muscular activity varied with respect to the slope angle, while the HR increased at a constant rate. During skiing exercise, functional activities change at every turn of skiing and at the relationship between skiing and ski lift riding, then finally degenerated for a whole day. At the beginning, motor command controls the cardiovascular and muscular activities, after several trials later the peripheral reflex such as mechano- and metabo- reflex play a significant role [3]. Hence, the autonomic nervous activity is affected by different factors as a function of time. Furthermore, the time-scales of those changes range from several ten seconds to several hours. It is the same story for recognizing the peripheral fatigue from surface ME signals during exercise.

We are trying to establish snapshot evaluation of such functional activities during exercise. First of all, we have to identify dominant factors at each phase after estimating time-varying behavior of several manifestations of activities. Then, we focus on the event related activities in order to synchronize the different time-scales: for example, the periodical change in the cardiovascular activity during ski lift riding induced by the preceding skiing exercise or the temporary change in the cardiovascular activity after dynamic muscle contractions during skiing. Measurement designed for the snapshot evaluation depends on the time-varying features of a target function. We, therefore, developed a radio controlled remote data acquisition system that allows us to obtain the biosignals at any time and any location. Regarding the analysis for the snapshot evaluation, we have to handle the time-varying behavior of biosignals at several different time-scales. Moreover, a specific biosignal does not always show the significant role. Therefore, multivariate analysis, multivariable time-series analysis, or multiscale time-series analysis seem to be suitable.

For a whole day, we traced the time-varying behavior of evaluation indices in different time-scales as a function of skiing exercise trial. For studying the relationship between skiing and ski lift riding, we used the Wavelet analysis and compared the dominant frequency components in HRV. At every contractions of skiing, we applied a multivariable ARX model for evaluating the correlation between muscle activities and HRV. Furthermore, we used the principal component analysis (PCA) of ME parameters and HRV to reveal the dominant components in functional activities during skiing. The PCA shows the differences at each phase during skiing, arranging redundant information on functional activities.

II. METHODS

A. Time-Varying Behavior of HRV

An instantaneous HR time-series, in beat per minutes, was transformed into the HRV by uniformly resampling the third-order spline interpolated original nonuniform R-R interval time-series. In general, the frequency range around 0.04 Hz or around 0.1 Hz, the low frequency region, has been widely accepted to show the increased sympathetic and parasympathetic tones. The high frequency region (0.15-0.5 Hz), on the other hand, relates to the respiratory activity and a sign of parasympathetic activity.

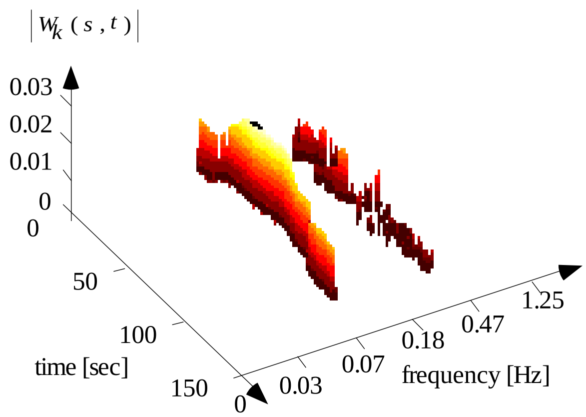


Fig. 1. Time-courses of target HRV frequency components.

We applied the Wavelet analysis for each 2-min of HR time-series during skiing and ski lift riding in order to classify the time-varying behavior of the sympatho-vagal interactions within each phase [4]. Assuming the HRV is given by

$$g(t) = \sum_{k=1}^{K} \frac{\alpha_k(t)}{2} \exp[i\theta_k(t)] + e(t) , \tag{1}$$

the continuous Wavelet transform is

$$W_k(s, t) = \frac{1}{s} \int \frac{\alpha_k(\tau)}{2} \exp[i\theta_k(t)]\, \psi(\frac{t-\tau}{s})\, d\tau . \tag{2}$$

Note that $e(t)$ is residual and $\psi(*)$ is a mother function. We are able to trace several local frequency component peaks, $\alpha_k(t)/2$ and $\theta_k(t)$, at limited frequency ranges, by screening the peak of $|W(f, t)|$ on the frequency axis at each time t (**Fig. 1**). Thus, the time-courses of the target HRV frequency components are obtained by tracking these local peaks after applying the Hamming window function to target frequency ranges. As a result, the Wavelet analysis reveals the dominant components in the HRV during each phase of exercise. However, we found the discontinuity of local frequency components of HRV at several time instants [4]. Thus, as a practical index to represent the different sympatho-vagal balance between skiing and ski lift riding, we averaged frequency and amplitude of the dominant components of the HRV, that is

$$\alpha \text{ and } f = d(\theta/2\pi)/dt, \tag{3}$$

within 2-min.

B. Multivariate Analysis of Biosignals

We have used the principal component analysis (PCA) to arrange the redundantly distributed information on functional activity from several biomedical signals [5].

Let us assume that $\boldsymbol{g}_n(l)$ consists of all of the normalized parameters at the l-th phase in a trial and $\boldsymbol{R}(l)$ is the correlation matrix of $\{\boldsymbol{g}_n(l)\}^N_{n=1}$. Note that n means the local time index for HRV and ME parameters in a phase. The eigenvalues $\{\lambda_m\}^M_{m=1}$ obtained from $\boldsymbol{R}(l)$ indicate the statistical structure of the distribution of $\{\boldsymbol{g}_n(l)\}$. That is,

$$\lambda_m = \sigma^2_m \tag{4}$$

where σ^2_m is the variance of the m-th principal component, PC_m, such that

$$z_m = \phi_m^T \boldsymbol{g} \tag{5}$$

at the l-th phase, where ϕ_m is m-th eigenvector. Since the components of ϕ_m were not fixed during dynamic movement, the time-varying features of the PCA indices need to be evaluated. To represent the above features, we focused on the components of ϕ_1 as a function of the trial number.

C. ARX Model

At each turn during skiing, we estimated ARX parameters for the system in which the input signals are ME parameters and the output is the HRV. The multivariable-inputs and one-output ARX model with white noise $\{\varepsilon_n\}$ is given by

$$y_n + \sum_{i=1}^{p} a_i y_{n-i} = \sum_{j=1}^{q} \boldsymbol{b}_j^t \boldsymbol{x}_{n-j-d} + \varepsilon_n , \tag{6}$$

where y_n and $\boldsymbol{x}_n$ are the output vector and the input vector at time n, respectively. Moreover, $\{a_i\}^p_{i=1}$ and $\{\boldsymbol{b}_j\}^q_{j=1}$ are coefficients of AR part and extra input part. Note that the index d means the time delay in the system. We estimated ARX parameters by the least-squares estimation using the Matlab System Identification Toolbox.

III. Experiment

We developed a battery supported radio controlled remote data acquisition system to measure biosignals at any time and any location. The system includes a sub notebook computer with a PCMCIA type AD convertor. The data acquisition program starts data acquisition process of 2-min when the trigger signal is received. Then, it waits the next trigger signal again. We simultaneously monitored the ECG and ME signals during skiing and the ECG during ski lift riding. Three male subjects participated in our experiment on separate days after they were informed of the experimental procedures and risks associated with the muscle fatiguing efforts. Ten to fifteen trials per day were performed for around six hours including the lunch break. A trail of skiing exercise consisted of about 3 minutes of skiing and 10 minutes of ski lift riding and the preparation for measurement. The distance on the lift path was 1364 m.

The gains of the amplifier were 46 dB (a highcut frequency f_c was 1 kHz and a time constant t_c was 0.5 s) for ECG recording, and 74 dB (f_c was 1 kHz and t_c was 0.5 ms) for surface ME signals. ECG and ME signals were sampled at 5 kHz and recorded directly into the hard disk of a sub notebook computer through the AD convertor with the resolution of 12 bits.

The HRV was obtained after detecting the R-waves and interpolating the beat-to-beat intervals by the spline function. The resampled frequency was 4 Hz. Two minutes of HRV was analyzed for the limited frequency bands ranging from 0.03 to 0.17 Hz for low-frequency-related (LF) and 0.3 to 0.7 Hz for high-frequency-related (HF) components. The Gabor function was selected as a mother Wavelet. We evaluated HRV indices, α and f in (3), at each 2-min phase. The ARV and MPF were estimated every 409.6 ms during skiing. The MPF was calculated during the frequency ranging from 5 to 500 Hz. For estimating the ARX parameters, the orders of multivariable ARX model was determined empirically: that is, p = 10, q = 9 for ARV, q = 8 for MPF, and d = 2. Fifty second of HRV, ARV, and MPF time-series were segmented from the first half of a skiing trial. In order to apply the PCA to HRV, ARV, and MPF time-series (N = 3), we first of all resampled them at sampling frequency of 4 Hz. Then we analyzed them every one minute (l = 1, 2): that is the number of samples, N, for PCA was 240 samples.

IV. RESULTS

A. Time-Varying Behavior of HRV

The R-R interval during a ski lift riding was larger than that during skiing. The amplitude of HRV during a ski lift riding increased as the function of trial [4].

Figure 2 shows the mean of $|W(f, t)|$ averaged in 2-min for high and low frequency-related bands with respect to time. Generally, the amplitude was higher for the LF component than for the HF component. In each trial, the amplitude increased during a ski lift riding phase and decreased during a skiing phase. The periodic change became prominent approaching the final trial of the day. These results were almost the same as those by the short-term Fourier transform. The behavior, however, did not show the expected sympathetic activity during skiing because the amplitude was low. Thus we tried to represent sympathetic activity in terms of the frequency of HRV components.

Figs. 3(a) and (b) showed the time-varying behavior of the frequency, f_{HF} and f_{LF}. The filled square represents the mean frequencies during ski lift riding and the open square shows the mean frequencies during skiing. We divided 2-min trial into two one-min segments because the slope was steep at the beginning, then gentle toward the finish point of a trial. The behavior of f_{HF} fluctuated around the base line. The frequency was higher during skiing than during ski lift riding for f_{HF}. The behavior of f_{LF} had a peak at the 13th trial and then the frequency decreased as the function of time.

B. Relationship between HRV and ME signals

Figure 4 showed the results of the PCA applied for biosignals during skiing. The dominant components of the 1st eigenvector were HRV and MPF. On the other hand, ARV was dominant in the 2nd principal component. During first one-min, the dominant components disappeared as the number of trials increased. That is, ARV joined the 1st principal component during last trials. Note that the $prop_1$ and $prop_2$ were around 41 % and 34 %, respectively.

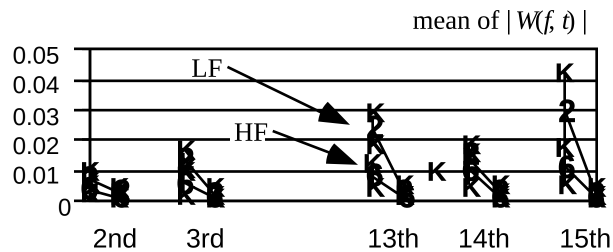
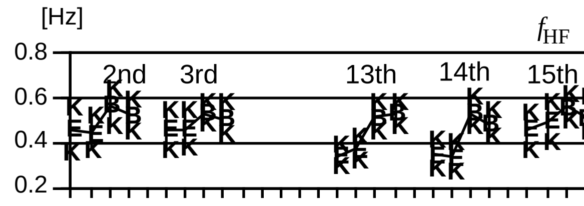
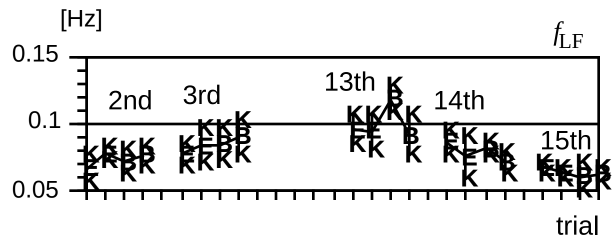


Fig. 2. Time-course of the HRV components.



(a) mean frequency of HF component



(b) mean frequency of LF component

Fig. 3. Time-course of the frequency of HRV components.

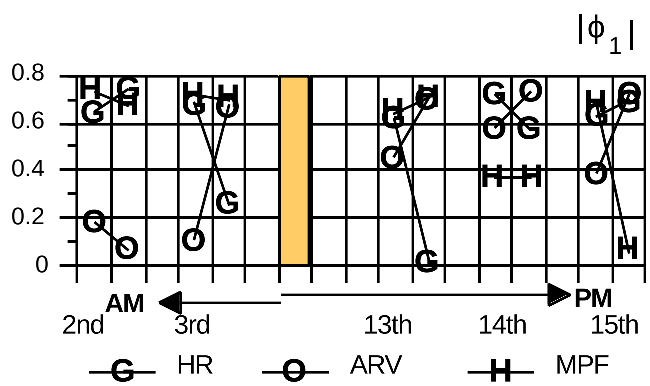


Fig. 4. Time-series of components in the 1st eigenvector.

Figure 5 demonstrates the amplitude of $H_{ARV}(\omega)$, as an input was ARV and an output was HRV, estimated by the ARX model. Note that another input was MPF. We estimated $H_*(\omega)$ where the R-R interval decreased rapidly. As a result, there was a plateau in the frequency band ranging from 0.5 to 1.5 Hz at 15th trial, whereas the amplitude was rather flat at the 2nd trial. Actually, we found a peak at around 1.2 Hz in the AR spectrum of ARV and also a peak around 1.3 or 1.4 Hz in the HRV at 15th trial.

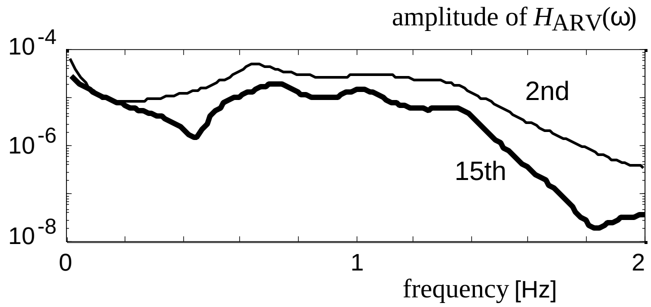


Fig. 5. Amplitude of $H_{ARV}(\omega)$.

V. DISCUSSION

A. Snapshot Evaluation

It needs some strategy to entirely interpret fatigue or degeneration of functional activities during exercise. We proposed the procedure based on the snapshot evaluation as follows: the radio controlled remote data acquisition system, synchronizing the biosignals with different time-scales for system identification, and selecting dominant components at each phase. Snapshot evaluation during a long-term exercise was useful to proceed the seamless measurement. However, it takes a lot of time to prepare for measuring multichannel biosignals and to handle a lot of original data.

B. HRV and Muscular Fatigue during Exercise

It has not been clarified how much the feeling of fatigue and/or the muscular fatigue would influence the HRV and the ME signals during long-term periodical skiing exercise. We observed the increase in the amplitude of LF component as the number of trials increased, during ski lift riding. This might be caused by the sympathetic activity to compensate the recover of blood fluid in the lower legs because there is no support for the lower legs during ski lift riding [6]. The results by the PCA and the ARX model during skiing demonstrated the relationship between HRV and muscular fatigue development. The rapid increase in the HR at the beginning of skiing possibly produced the results that HRV was a dominant factor in PC_1. During the first several trials, aerobic exercise induces the accumulation of metabolic byproducts. Metabolic byproducts would be removed by circulation during ski lift riding. After several repetitive trials, however, metabolic byproducts enough produced in the muscles. That is, the information occurred at peripheral was transmitted to the HR in order to adapt the strength and the level of exercise. When the functional activity exceeds the capacity, the feeling of fatigue might increase. The domination of ARV and HRV in PC_1 and narrowing the frequency band of $H_{ARV}(\omega)$ might be a sign of fatigue originated from the interaction between cardiovascular and neuromuscular activities, although other approach such as nonlinear system model should be considered.

VI. CONCLUSION

We showed the time-varying behavior of functional activities during skiing exercise by the dominant frequency components of HRV using the Wavelet analysis, the dominant factors selected by the PCA, and the ARX model. The frequency of LF bands of the HRV had a peak after around one-hour break, then decreased again toward the final trial of the day. Examining the features estimated by the PCA and ARX model during skiing, we found that the HRV and ARV became dominant factors during skiing as muscular fatigue developed. Consequently, appropriate combination of several information might be necessary to accomplish the snapshot evaluation of functional activities during a long-term skiing exercise.

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