RELATIONSHIP BETWEEN MOTION VECTORS OF VECTION-INDUCED IMAGE AND MULTIVARIATE BIOSIGNALS UNDER VISUAL TASKS

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Abstract: **The purpose of our study is to reveal the influences of video images on the autonomic function quantitatively. As an approach, we applied the principal component analysis to multivariate biosignals including the R-R interval, blood pressure, and respiration. The results showed that the dominant frequency of the time-series of the second principal component score occurred around 0.1 Hz while viewing a stress-inducing image video. Moreover, we estimated the motion vectors from the video images. The motion vector closely correlated with the second principal component score in the sections where the motion vector changed the vibration rate.**

Keywords: **Video images, motion vector, vection, principal component analysis, mental stress**

I. INTRODUCTION

There have been many video formats, screen size, resolution and frame rate, on the Internet and in digital broadcasting. As Harding reported [1], video image factors which evoked photosensitive seizures has been well analyzed, knowledge on the visual factors which would cause motion sickness or related unpleasant influences on humans are wanting. Conventional studies have handled multivariate biosignals to evaluate mental stress under visual tasks. However, quantitative evaluation of the relationship between the characteristics of the stressors (video images) and multivariate biosignals has not yet been studied. In this paper, we first of all applied the principal component analysis to multivariate biosignals, then investigated the relationship by using the motion vectors of the video image and the principal component scores of multivariate biosignals.

II. METHODOLOGY

A. Experimental Procedure

Five healthy elderly subjects (from 52 to 71 yrs. old) and six elderly subjects with mild hypertension or diabetes mellitus (5 males and 1 female from 50 to 71 yrs. old) participated in the experiments. The subjects were informed of the risks involved in advance, and their ECG, blood pressure, and respiration were monitored during the experiments. For the 18-min length visual tasks, eleven different contents of sports images with vection were used. In particular, we selected the image of mountain bike riding because almost all the subjects felt unpleasant conditions during and after watching the video image. Note that the video camera was attached at the top of the mountain bike handle. The image was back-projected on an 80-inch screen by the video projector (TH-L795J, Panasonic) with XGA and 1400 ANSI lumen. The distance between the projector and the screen was 2 m and the illumination was 10 lux. The ECG was measured on the chest and the blood pressure was measured by a tonometry method (JENTOW770, Colin). The respiration was measured with sensors around the chest and the abdomen. These biosignals were sampled at the rate of 1000 Hz with a 16-bit resolution.

As a reference, we measured ECG data during cycling. This was an actual field exercise. The length of the circuit path was approximately 900 m and there was a steep uphill near the middle point of the path. An experiment was composed of six consecutive 2.5 minutes of cycling with 2-minute rest trials. The healthy young subjects (from 21 to 24 yrs. old) were asked to pedal a bicycle at 60 rpm as much as possible and to turn left at each corner. The incline changed at the second (from down to up) and third (from up to down) corners. The ECG was sampled at the rate of 2000 Hz with a 12-bit resolution.

B. Principal Component Analysis

The features of mental conditions do not always appear as specific biosignals with the progression of time. Thus, we arranged mental stress-related information from several biosignals by the principal component analysis (PCA). Assuming $\{\xi_k(l)\}_{l=1}^{L}$ denotes the normalized time-series of L samples of a biosignal k, the biosignal vector at frame l, composed of K kinds of biosignals, is defined as

$$\boldsymbol{g}(l) = \left\{\xi_1(l), \xi_2(l), \cdots, \xi_K(l)\right\}^T. \tag{1}$$

Calculating the $K \times K$ correlation matrix from $\{\boldsymbol{g}(l)\}_{l=1}^{L}$, the eigenvalues $\left\{\lambda_p\right\}_{p=1}^{P}$ and the $K \times 1$ eigenvectors $\left\{\varphi_p\right\}_{p=1}^{P}$ are obtained ($P \le K$). Using $\boldsymbol{g}(l)^T$ and φ_p, the p-th principal component (PC) score $z_p(l)$ is calculated as follows:

$$z_p(l) = \boldsymbol{g}(l)^T \varphi_p. \tag{2}$$

Specifically, 50-sec multivariate biosignals including the RR interval, blood pressure, and respiration were processed by the PCA at each consecutive overlapping segment to obtain the time-series of the PC scores. Note that the resampling frequency of the PC scores was adjusted for the frame rate of the video image, that is, 30 frame/sec. We then analyzed the PC scores by the continuous Wavelet analysis to extract the autonomic nervous activity-related information.

C. Motion Vector

We investigated a candidate of the stressor in the vection-induced video image by the motion vector that is used in the image compression technique. We estimated the motion vector by the block matching method [2]. Assuming the motion vector in an $N \times N$ block as

$$\boldsymbol{v} = \left[v_x, v_y\right]^T, \tag{3}$$

the motion vector between consecutive frames is obtained by

$$(v_x, v_y) = \underset{i,j}{\mathrm{argMin}} \sum_{x=0}^{N} \sum_{y=0}^{N} \left| f_l(x,y) - f_{l-1}(x+i, y+j) \right|. \tag{4}$$

Note that $f_l(x,y)$ is an image value, (*i*, *j*) is a pair of range parameters for searching the similar property in a block between *l* and *l*-1 frames, and $\underset{i,j}{\arg Min}(\alpha)$ determines the motion (*i*, *j*) that minimizes α within $-N^2/2 \leq i, j \leq N^2/2$.

We estimated the motion vectors in each section from the image size of 352×288 pixels. Note that the whole image was divided into 25 (5×5) sections. Moreover, the motion vector was estimated in the block of 8×8 pixels and then averaged in each section to estimate the averaged motion vector. Finally, we obtained the time-series of the correlation coefficients among several biosignals, the PC scores, and the averaged motion vectors in each sliding window with a 10-sec interval. The sliding window was shifted every frame.

III. RESULTS

Fig. 1 shows the RR interval (a) while watching the mountain bike riding video and (b) during actual bicycle exercise. Both scenes for the subjects were similar, although the subjects, types of stresses, and environments differed. The arrows show the start times of each event (up-down and turn). In the mountain bike riding video, several events consist of quick motions after temporally motion pauses. For aged subjects, the RR interval varied randomly. The periodical wave in the RR interval was sometimes obstructed by temporally emerging other waves. The variations for healthy aged subjects were larger than those for subjects with mild hypertension or diabetes mellitus. During actual cycling, the time-varying behavior of the RR interval clearly changed at the second corner, because the incline changed from downhill to uphill with a left turn. At 6th trial, the variations became small due to fatigue. From this point of view, the response of the subjects while watching the mountain bike riding video was different from the autonomic responses.

Fig. 2 shows the biosignals and PC scores while watching the mountain bike riding video. We selected biosignals during the downhill riding scene with the abrupt downs and the left turns based on subjective proposals. The original biosignals included several types of periodical features and temporally emerging other waves. On the other hand, the second PC score extracted a periodical feature, while the first and third PC scores still included temporally emerging other waves. Hence, we easily estimated the frequency components of the second PC score by the Wavelet analysis. As a result, we observed a frequency component of around 0.1 Hz under unpleasant feeling conditions. The feature was clearer for healthy subjects than for subjects with mild hypertension or diabetes mellitus.

Fig. 3 demonstrates the motion vector and the correlation coefficient between the motion vector and biosignal parameters as a function of time. The view positions ranged from a close section to a distant section. The correlation coefficients at several sections of the video image were studied. Note that the correlation coefficient between the second PC score and the blood pressure was high (Fig. 2). We observed a negative correlation at the intervals around 35 sec and 65 sec, without the view positions. At these intervals, the motion vector varied from quick vibration to slow motion. On the other hand, there was no correlation where the motion vector showed a steady quick vibration.

IV. DISCUSSION

The autonomic response of the subjects while watching the mountain bike riding video was apparently different from the responses during actual cycling (Fig. 1). Under vection-induced visual tasks, the RR interval rhythm was temporally obstructed by other waves. However, the measured biosignals did not always show the same results. Hence, arranging the biosignals by the PCA was effective to track the autonomic nervous activity-related information from several types of biosignals that were measured simultaneously. The second PC score extracted a frequency component of around 0.1 Hz that could be related to the Mayer wave [3]. Actually, the second PC score and the blood pressure were quite similar to each other during the interval (Fig. 2). Note that healthy elderly subjects did not show the clear Mayer wave [4]. Hence, this finding should be confirmed by further physiological studies.

The responses were clearly caused by the different factors included in the video image. One of the factors was the video content, a scene of mountain bike riding with the abrupt downs and the left turns. This vection-induced video image contained the differences between the scene captured by the camera equipped on the handle of the bicycle and the actual head motion of the rider predictively controlled by the inner-model. The evidence is, however, difficult to assess. Instead, we investigated another candidate of a stressor that could be included in the video image. The motion vector represents a structure of a scene at each section in an image screen, that is, the frame rate, the vibration of objects in the image screen, etc. Thus, the motion vector is rather a contents-free factor.

The motion vectors were correlated with the second PC score and the blood pressure at several intervals of the mountain bike riding video image, without the view positions (Fig. 3). The elderly subjects with mild hypertension or diabetes mellitus did not always show this responses, probably depending on the degree of the disease. At the intervals where the correlation coefficients were significant, it was found that the motion vector had a specific temporal pattern: quick vibration to slow motion. In the mountain bike riding video image, changes in the motion vector reflected the driving strategy of the mountain bike (quick motion after a temporally motion pause). However, this type of change could be included in other video images. As a result, a particular vibration pattern of the motion vectors could induce unpleasant conditions on humans. Since age-related disappearance of the Mayer wave was reported [4], investigation of such factors in video images is important.

V. CONCLUSION

We studied the influence of vection-induced video images on humans. The PC score was effective for extracting the meaningful information from the multivariate biosignals. That is, the second PC score showed a clear periodical variation with respect to time, and the period was correlated to the rhythm of blood pressure-related Mayer wave. We then investigated a candidate of the stressor in the video image by the motion vector. The results showed that the mountain bike riding video image induced unpleasant feelings and that the motion vector was negatively correlated with both the second PC score and the blood pressure at specific intervals of the image sections. At these intervals, the motion vector varied from quick vibration to slow motion. On the other hand, there was no correlation where the motion vector showed a steady quick vibration. Hence, the vibration pattern of the motion vector could be important to assess the influence of a vection-induced video image. However, we have not yet concluded whether the unpleasant feeling was caused by the content of the vection-induced image or the structure of the image scene (the frame rate, the vibration of objects, etc). Moreover, further studies are required in terms of the motion sickness [5].

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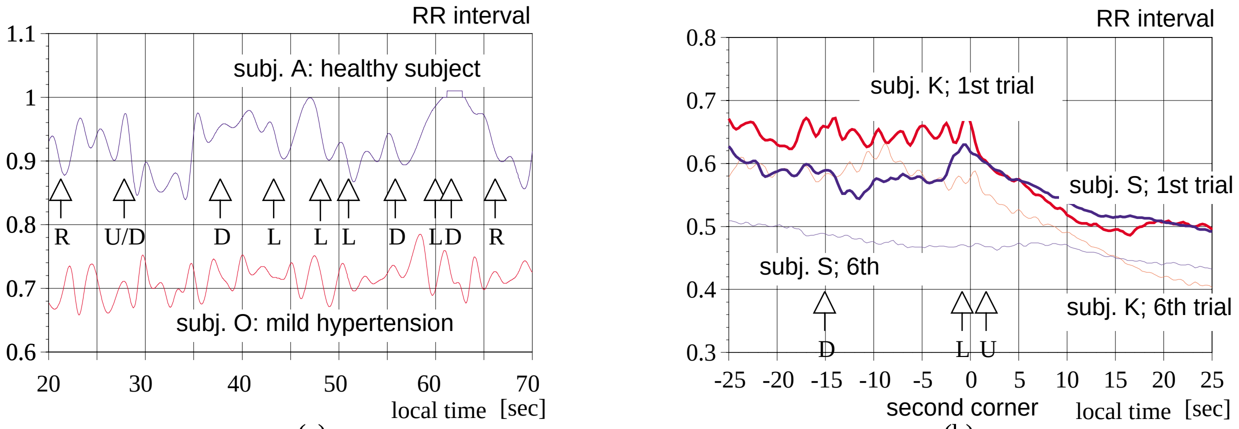
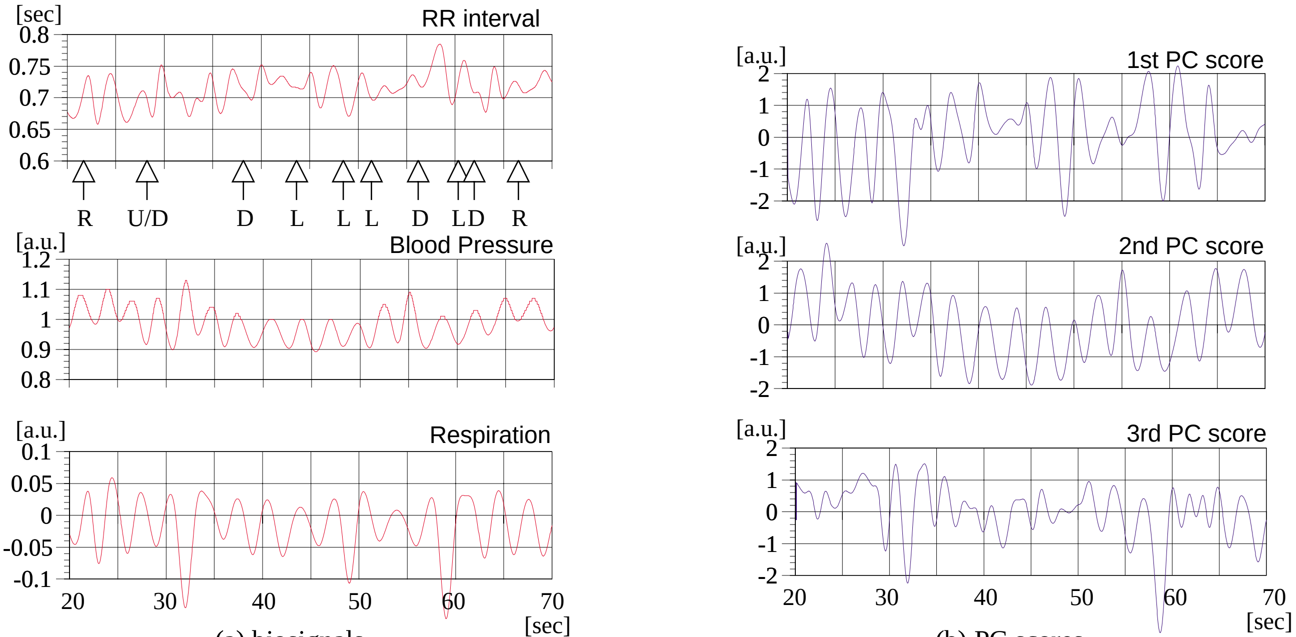


(a)

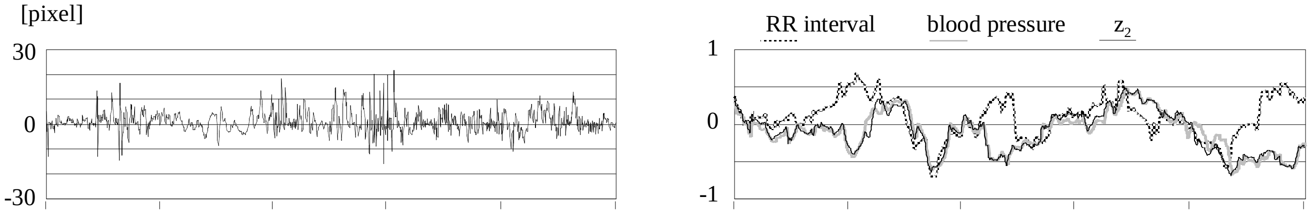
(b)

Fig. 1. RR interval (a) while watching the mountain bike riding video and (b) during cycling exercise. In RR interval, R, U/D, D, and L mean turn right, move upward and immediately downward, move downward, and turn left, respectively.

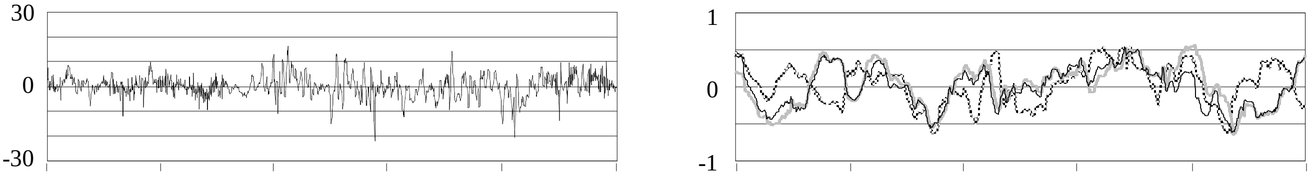


(a) biosignals (b) PC scores

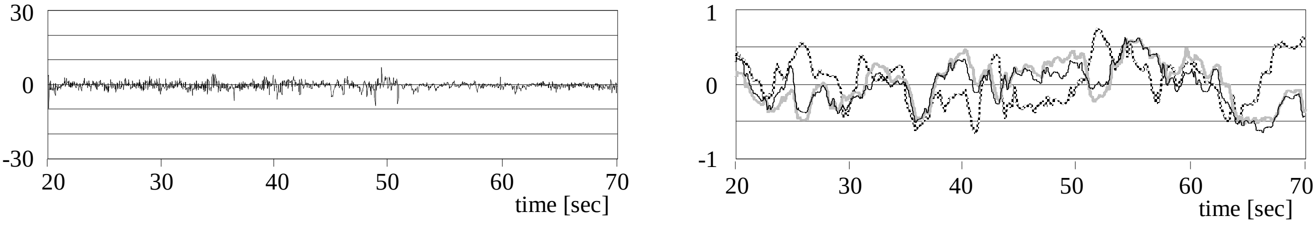
Fig. 2. Time-series of RR interval, blood pressure, and PC scores. In RR interval, R, U/D, D, and L mean turn right, move upward and immediately downward, move downward, and turn left, respectively (subject O).



distant-range view position at $(b_x)_{1,1}$



middle-range view position at $(b_x)_{3,3}$



close-range view position at $(b_x)_{5,3}$

(a) averaged motion vector of v_x (b) correlation coefficient between v_x and biosignals

Fig. 3. Horizontal motion vectors (plus left / minus right) and correlation coefficients between motion vector and biosugnals at each section (subject O).