A Modeling Approach to Investigate the Relationship between Motion Sickness Severity and Visual Motion

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ABSTRACT

In this study, dynamic characteristics between image motion and severity of visually induced motion sickness (VIMS) was modeled as a Hammerstein model, which consists of a static nonlinear function followed by a linear system. The results indicate the change in subjective VIMS score may be estimated from image motions.

1 INTRODUCTION

Recent rapid development in display technologies has exposed many people to new display environments such as widescreen TV sets with high resolution and head mounted displays. However, there are concerns about adverse effects of visual stimulation on humans. The International Organization for Standardization (ISO) has publicized the document of recommendations for reducing the potential visual discomfort and visual fatigue experienced during viewing of stereoscopic images under defined viewing conditions (ISO 9241-392:2015).

Visually induced motion sickness (VIMS) is also encountered during watching a moving image displayed on a wide field display or screen [1]-[3]. In order to reduce the risks for VIMS, it is important to investigate the relationship between VIMS and each component of video motion such as transition and roll. Ujike et al. reported the static effects of global motion (GM) which is consisted by roll, pitch and yaw [4]. Because the effects of visual stimuli have dynamic response such as accumulation and recovery, it is desirable to reveal the dynamic response from exposure of motion image to change in severity of VIMS. Our group has reported that time and quantitative resolution of subjective score of the severity can be improved by using physiological indices [5]. Furthermore, it has also been indicated that a simple linear model can represent relatively well the dynamic relationship between the continuous change in a subjective score and the GM [6]. However, the model does not contain nonlinear characteristics such as dead band. The aim of this study is to model the dynamic relationship between GM vectors (GMV) of video and severity of VIMS by a nonlinear dynamical system.

2 METHODS

2.1 Experiments

Fig. 1 shows the schematic illustration of the experiment carried out in this study. The subjects watched the video image displayed by a LC display (GD-463D10; Victor Company of Japan, Limited). A size and resolution of display ware 46inces and 1920x1080, respectively. The viewing distance was 0.86m which is 1.5 times as height as the display. The illumination in the room was 10 lx.

Electrocardiogram (ECG), plethysmogram (PPG) at left finger and continuous blood pressure at radial artery (RBP) were recorded with a sampling frequency of 1 kHz using a 16-bit A/D converter (MP150; BIOPAC System Inc.) while watching the video. The subjective score (SS) of 4-level-graded (0 to 3) severity of VIMS was also recorded every 30s. Before and after the exposure, each subject filled out the Simulator Sickness Questionnaire (SSQ) [7].

We used two video images. One consisted of 5min still image, 8min CG video image including various motion and 2min still image (movie A) and the other consisted of same setup with different motion components (movie B). The subjects watched the movie A or the both.

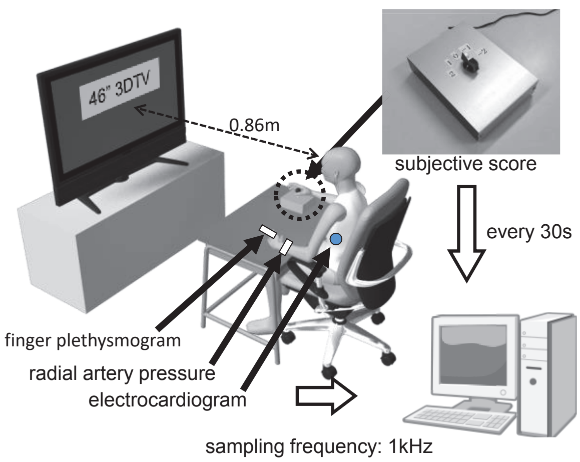

Fig. 1 Schematic illustration of the experiment

A total of 20 subjects (10 males, 10 females, 21.0±0.7years) participated in the study. After the approval of the ethical committee of Fukushima University, informed consent was obtained from all the participants before the experiment.

2.2 Preprocessing of Physiological Data and Estimation of Subjective Score

Instantaneous heart rate (*HR*) was calculated from the reciprocal of time interval between R-wave on the ECG signal. Arterial pulse wave transmission time (*PTT*) was defined as the time interval from the peak time of the ECG R-wave to the point at which the PPG signal begins to rise. After obtaining beat to beat data of *HR*, mean blood pressure (*BP*) and *PTT*, they were interpolated by cubic spline functions to be time-continuous functions, and were re-sampled every 0.2s.

In order to improve resolution of measured subjective score for system identification, the multiple regression equation which estimated subjective score from physiological indices was calculated at every subject. A forward stepwise linear regression was used to determine the most promising independent variables for the model identification. The candidates of explanatory variables were following 9 parameters.

- Mean heart rate (HR_m)
- Mean blood pressure (BP_m)
- Mean value of pulse wave transmission time (PTT_m)
- Coefficient of variation of R-R intervals (*CVRR*)
- Low frequency power of heart rate variability (*LF*)
- High-frequency power of heart rate variability (*HF*)
- *LF*/*HF*
- Maximum cross-correlation coefficient between heart rate and blood pressure ($\rho_{\max}$)[8]
- Auto-regression coefficient of the linear model from RBP to PPG (a_1).

These indices were calculated with the time window of 30s shifted every 10s.

2.3 System Identification between global motion vectors and VIMS severity

The aim of this study is to model the dynamic relationship between GMVs of video and severity of VIMS. In order to quantify the GMVs of the movies, root mean squared (RMS) values of image rotation speed around three axis of head coordinate system were calculated at every 10s [9].

In this study, the model which represents the relation between GMVs and estimated subjective score (SS) was identified as following Hammerstein model [10][11],

$$SS(k) = \sum_{i=1}^{3} \frac{B_i(q^{-1})}{A_i(q^{-1})} f_i\big(x_i(k)\big) + e(k) \qquad (1)$$

where, k denotes the discrete-time index, $B_i(q^{-1})$ and $A_i(q^{-1})$ are polynomials in shift operator q^{-1}, x_i are RMS of GMVs representing pan, tilt and roll, $B_i(q^{-1})/A_i(q^{-1})$ represents linear transfer function, f_i is static nonlinear function and $e(k)$ is the residue. In this study, the following sigmoid function is used as nonlinear function in order to represent dead band and saturation characteristics.

$$f_i(x_i) = \frac{\alpha_i}{1 + e^{-\beta_i(x_i-\gamma_i)}} + d_i \qquad (2)$$

The model parameter was estimated by using iterative search algorithms to minimize the loss function.

3 RESULTS AND DISCUTTIONS

The data sets of six participants whose subjective scores were always 0 and two participants whose physiological indices could not be calculated because of severe disturbance were excluded from analysis. Fig. 2 shows the relationship between mean values of measured *SS* and those of estimated values using multiple regression equations for movie A. The root mean square error was 0.20 and correlation coefficient *R* was 0.83. This result indicated that the change in *SS*

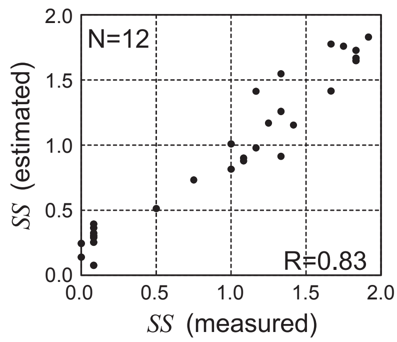

Fig. 2 Relationship between mean values of measured subjective score and estimated values via physiological indices (movie A)

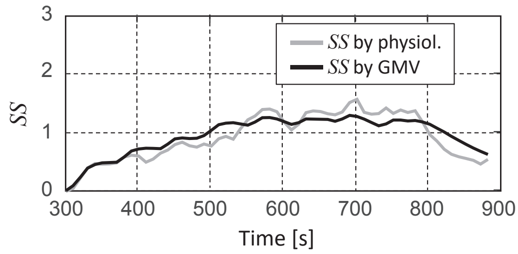

Fig. 3 *SS* estimation result via global motion vector (movie A)

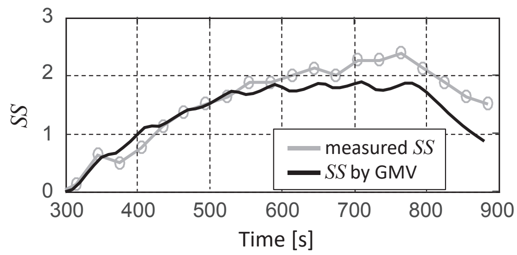

Fig. 4 *SS* estimation result via global motion vector of movie B using the same model as Fig. 3

can be estimated from physiological indices though the types of explanatory variables of the multiple regression model had individual differences. Therefore, a time series of *SS* was able to be obtained with higher time and quantitative resolution than a measured score.

Fig. 3 shows the estimation result for mean change in continuous subjective score by identified Hammerstein model. The correlation coefficient was 0.93. Fig.4 shows the comparison of the change in measured subjective score in movie B and the output of the model which was identified using the result of movie A with the global motion vector of movie B as input. The change in *SS* can be simulated by only GMV of viewing image though underestimation occurs at the latter part. This result may indicate that the proposed Hammerstein nonlinear model can roughly estimate the change in degree of VIMS from global motion vectors of a video image. Furthermore, the sigmoid function which is static nonlinear of the model may able to represent the dead band of each motion component. In order to identify the model parameters of the static nonlinear part, however, it is necessary that the viewing image for experiment has sufficiently wide range of GM amplitude.

4 CONCLUSION

In this study, a model based approach to evaluate the effect of VIMS induced by actual motion image, which includes various and complex motion components, was introduced. First, the continuous change in the subjective score of the degree of VIMS was obtained from the multiple regression equation consisting of physiological indices. Second, the relationship between the subjective score and video global motion was identified as a Hammerstein model which consist of a static nonlinear function followed by a linear system. The approach has following characteristics: a) the continuous change in the subjective score of VIMS is obtained with higher time and quantitative resolution than the intermittently measured subjective score, b) the model can represent the dynamic behavior of VIMS such as accumulation and recovery, c) the nonlinear part of the model can represent gain characteristics of the influence of each motion component on VIMS with nonlinearity such as dead band and saturation. The results indicate that model can effectively represent the change in degree of VIMS from GMV. In future works, much more data sets from experiments using motion image having a wide range of amplitude and frequency of motion are necessary to obtain a more accurate model.

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