A Practical SSVEP-based Algorithm for Perceptual Dominance Estimation in Binocular Rivalry

Kazuo Tanaka, *Fellow, IEEE,* Motoyasu Tanaka, *Member, IEEE,* Toshiya Kajiwara, and Hua O. Wang, *Senior Member, IEEE*

***Abstract*—This paper presents a practical algorithm for perceptual dominance estimation in binocular rivalry. The algorithm using steady state visual evoked potentials (SSVEP) effectively realizes a real-time estimation of perceptual dominance in binocular rivalry from electroencephalogram (EEG) signals. For accuracy of estimation, the algorithm utilizes the EEG spectrogram obtained via the short-time Fourier transformation with a short time analysis window. More importantly, the algorithm focuses on the acceleration (second order time differential) of the spectrogram difference between SSVEP of left-eye stimulus and that of right-eye stimulus, where the left-eye stimulus and the right-eye stimulus are separately displayed for left-eye and right-eye, respectively, with different-flashing-frequency visual stimuli of dissimilar images. Experimental results demonstrate the utility of the algorithm, particularly, the importance of introducing the acceleration of the spectrogram difference. With the simplicity of the algorithm, it is in fact suitable to accurately measure binocular rivalry without verbal communications in real-time environments.**

***Index Terms*—acceleration of spectrogram difference, binocular rivalry, electroencephalogram, steady state visual evoked potentials.**

I. INTRODUCTION

BINOCULAR rivalry [1], [2] is known as the phenomenon that humans cannot simultaneously perceive dissimilar images from the left and right eyes. According to [3], binocular rivalry is a puzzling phenomenon:when two distinct images are presented to the eyes, the percept changes stochastically from one image to the other, despite the unchanged stimulation of the eyes. This makes rivalry paradigms well suited to study the neural sources of conscious perception [4]. In addition, binocular rivalry is considered useful for studying perceptual selection and awareness in both human and animal models. In other words, binocular rivalry is considered an effective tool for investigating the processes underlying visual awareness [5]. Thus, it is possible to investigate locus of awareness, perceptual selection and unconscious processing by using binocular rivalry. This paper is motivated by an interest in practically utilizing the puzzling phenomenon occurred by binocular rivalry. Although there exist a large number of studies on binocular rivalry, e.g., [6]-[12], most of these studies are from the fields of psychology, neuroscience, brain science and/or vision perception. Recently, a technique [13] to predict subsequent stability in perceptual rivalry has been reported. The technique realizes its prediction by observing the pupil diameter in the optokinetic nystagmus and does not directly utilize EEG signals. Although the work [12] investigated binocular rivalry with the steady state visual evoked potentials (SSVEP), the work did not aim at estimating perceptual dominance in binocular rivalry. It mainly focused on an observation of the waxing and waning of the visual evoked potential (VEP) amplitudes during binocular rivalry. To the best of our knowledge, there are few studies on estimating perceptual dominance in binocular rivalry using only EEG signals even though EEG based estimation techniques may be widely applicable to measuring binocular rivalry in non-verbal human subjects (or possibly animals) in real-time environments. A real-time perceptual dominance estimation algorithm for binocular rivalry was presented only in [14]. The algorithm presented in [14] was based on a typical SSVEP technique [15]. However, this paper will demonstrate that there is still room for improvement in the estimation accuracy of the algorithm [14] and indeed will bring new ideas to significantly improve the accuracy of estimating perceptual dominance in binocular rivalry over the existing approach. The new ideas are based on our hypothesis that the acceleration (second order time differential) of the spectrogram difference between SSVEP of left-eye stimulus and that of right-eye stimulus contributes to better estimation results. There exist remarkable issues supporting the hypothesis in the literature (e.g., [16]-[21]) on brain visual perception and computational visual models for the V1 receptive field. In fact, it is known that the V1 receptive field has high sensitivity for derivative visual-motion information. From this point, high-order derivative information of brain activity signals may be able to contribute to the estimation accuracy of the perceptual dominance, but higher-order derivative information (like jerk, more than second-order derivative information) is regularly contaminated by noises (artifacts) from a signal processing point of view and it may be unable to fully contribute to the estimation accuracy of the perceptual dominance. Marr [16] provided a framework to integrate knowledge from cognition and computation to understand vision and the brain. Since then, the derivative properties of visual perception in human brain have been frequently reported. The well-known motion energy model (that is a human visual model for motion information extraction) proposed by Adelson and Bergen [17] utilized four combinations of the spatial and temporal filters.

K. Tanaka, M. Tanaka, T. Kajiwara are with the Department of Mecahnical Engineering and Intelligent Systems, The University of Electro-Communications, Tokyo, 182-8585 Japan (e-mail: ktanaka@mce.uec.ac.jp; mtanaka@uec.ac.jp; toshiya.kajiwara@rc.mce.uec.ac.jp).

H. O. Wnag is with the Department of Mecahnical Engineering, Boston University, MA 02215, USA (email: wangh@bu.eud).

Manuscript received March 30, 2016; revised Manuscript received August 12, 2016.

The temporal filters with adjustable parameters to control the sensitivity for time response have high sensitivity for derivative vision-motion information (for example the temporal filter with relatively fast response in [17]). The resulting outputs from four combinations of the spatial and temporal filters in the motion energy model [17] clearly have a high correlation with cortical neural activity, i.e., EEG. For instance, a recent excellent work [22] achieved reconstruction (generated by mixing a large number of other movies with higher similarities) of natural movies (not static images) from brain activity. The work also utilized the motion energy model to reconstruct natural movies from brain activity signals. Very recently, Pavan [21] introduced a second order motion energy model for modelling fast forms of visual neural plasticity. Thus, the acceleration (second-order derivative) detection would be an appropriate way to bridge between visual perception and brain activity signals. These facts support that the derivative information (up to the second order derivative information) of EEG in both the time and frequency domains has a high correlation with visual perception. In this paper, we present an algorithm to verify the hypothesis in Section III and verify the hypothesis in experimental results of Section IV.

This paper presents a practical SSVEP-based algorithm for real-time and effective perceptual dominance estimation in binocular rivalry from EEG signals. For accuracy of estimation, the algorithm utilizes the EEG spectrogram obtained via the short-time Fourier transformation with a short time analysis window. More importantly, the algorithm focuses on the acceleration (second order time differential) of the spectrogram difference between SSVEP of left-eye stimulus and that of right-eye stimulus, where the left-eye stimulus and the right-eye stimulus are separately displayed for left-eye and right-eye, respectively, with different-flashing-frequency visual stimuli of dissimilar images. This paper also investigates the influence of colored stimuli in perceptual dominance estimation. This paper does not aim at discussing the color effects in binocular rivalry. The purpose is to show the utility of the proposed algorithm in both of the different color cases. In comparison with the existing approach [14], experimental results demonstrate the utility and applicability of the algorithm, and in particular, the importance of introducing the acceleration of the spectrogram difference. Furthermore, the experimental results indicate that the colored stimuli do not influence estimation results in both the existing approach and the proposed approach. Since the simple algorithm works at every 8 [ms] interval, it is actually suitable to accurately measure binocular rivalry without verbal communications (non-verbal human subjects or possibly animals) in real-time environments.

Visual awareness of not only humans [23] but also animals, e.g., monkeys (macaques) [24], [25], has been investigated by utilizing binocular rivalry. In other words, binocular rivalry is now considered as appropriate psychophysical evidence of visual awareness. In [24], two monkeys were trained to perform a categorization task by pulling one of two levers. For example, they were trained to pull and hold the left lever whenever a sunburst-like pattern was displayed and to pull and hold the right lever upon presentation of other figures (images of humans, monkeys, apes, wild animals, butterflies, reptiles, etc.) and various manmade objects. Thus, in most of studies, monkeys were trained either to gaze passively at rival patterns, or to report fluctuations in dominance [4]. However, as noted in [26], training monkeys to perform such behavioral tasks often requires substantial investment of time and effort. Descriptions and assessments of methods for training nonhuman primates in the laboratory are actually difficult in practice. Hence, monkey training techniques have typically been developed in an ad hoc fashion within individual laboratories. The estimation technique developed in this paper may be applicable to such monkeys' percept experiments without the requirement of training, instead of their ad hoc fashion. In addition, there exist a number of studies, e.g., [27], [28], on monkey SSVEP experiments. In fact, it is known that monkeys have M and P pathways and produce contrast response curves in electrophysiological studies that are very similar to the SSVEP functions like humans [29]. Thus, the estimation technique is applicable to investigate visual awareness without verbal communications.

This paper is organized as follows. Section II shows our experimental system for perceptual dominance estimation in binocular rivalry. Section III presents a new algorithm to verify the hypothesis and Section IV verifies the hypothesis through experimental results. Section IV also compares our algorithm with the existing algorithm. Finally, Section V summarizes the conclusions of the paper.

II. Experimental System

Section II presents the experimental setup for perceptual dominance estimation in binocular rivalry.

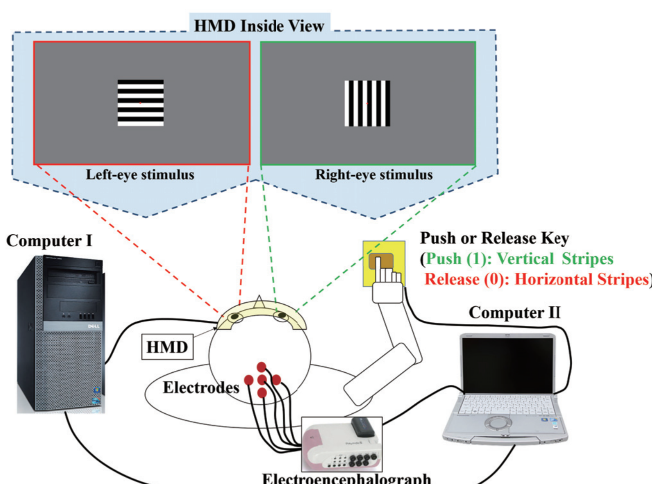

Fig. 1. Experimantal system for perceptual dominance estimation in binocular rivalry.

Fig. 1 shows the experimental system for perceptual dominance estimation in binocular rivalry. A pair of black-and-white pattern reversal visual stimuli (as used in many studies, e.g., [30]), with five equally spaced parallel bars, are employed in the experimental system. In the head-mounted display (HMD) inside view of Fig. 1, the left and right sides denote left-eye stimulus (horizontal stripes) and right-eye stimulus (vertical stripes), respectively. A pair of red-and-black and green-and-black pattern reversal visual stimuli is also considered as a colored version. As subjects' perceptual dominance records in binocular rivalry, subjects are required to press a key or release the same key according to perceiving results of either vertical stripes or horizontal stripes. The feedbacks from subjects are recorded as either vertical stripes (push the key:1) or horizontal stripes (release the key:0) at every interval. In addition, different-flash-frequencies for left-eye stimulus (horizontal stripes) and right-eye stimulus (vertical stripes) are employed to estimate perceptual results of either vertical stripes or horizontal stripes. In other words, by using a typical SSVEP detection method, it is possible to estimate perceptual dominance of either left-eye stimulus or right-eye stimulus. This is a key idea of the SSVEP-based algorithm for perceptual dominance estimation in binocular rivalry from EEG signals. The experimental system consists of an electroencephalograph (DIGITEX LAB. CO., LTD., Polymate II), an HMD (Sony Corporation HMZ-T1) and two computers (TWOTOP-BTO (CPU:Intel(R) Core(TM) i7-3770k(3.50GHz), Memory:8.00GB) and Panasonic Let's Note CF-S9 (CPU: Intel(R) Core(TM) i5 (2.53GHz), Memory:4.00GB)). The HMD is suitable to separately display different pattern and frequency visual stimuli for left-eye and right-eye via the well known side-by-side method. The upper part (HMD inside view) of Fig.1 shows black-and-white pattern reversal stimuli (Case 1) used in the experimental system, where the left and right sides denote left-eye stimuli and right-eye stimuli, respectively. Their spatial frequency is 2 [cycle/deg.] that is the same setting as in [12]. The size of each image is set so as to be that visual angle is 10 [deg.]. To investigate the influence of different color visual stimuli in the perceptual dominance estimation, we also provide another color version as a pair of two pattern reversal visual stimuli (Case 2). Fig.2 shows the two pattern reversal visual stimuli, where the left and right sides denote left-eye stimuli (red-and-black pattern horizontal stripes) and right-eye stimuli (green-and-black vertical stripes), respectively. We note that some previous works [6], [7] also utilized the same color patterns of red and green. We will show that the proposed approach gives better results than the existing approach [14] in both black-and-white pattern (Case 1) and the colored pattern (Case 2).

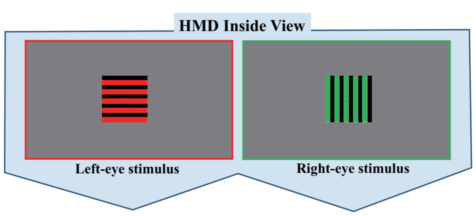

Fig. 2. Red-and-black and green-and-black pattern reversal stimuli (Case 2), (Left:left-eye stimuli Right:right-eye stimuli)

In the experiments, ten healthy subjects, with no visual and/or other abnormalities, are asked to perform the key press/release tasks according to perceiving either left-eye stimulus or right-eye stimulus. Informed consent was obtained from every subject according to the experimental procedures approved by the human research committee of University of Electro-Communications, Tokyo, Japan. Five electrode positions (PO_z, O1, O2, O_z, l_z) are selected according to the ten-twenty international electrode system [31]. We select earlobe (A2) and forehead (middle frontal-polar point) (F_{pz}) as reference and ground electrodes, respectively. The sampling rate for detecting EEG is 1000 [Hz]. To measure pure EEGs as much as possible, the impedance check is carefully performed, i.e., the impedances for all the electrodes are kept at least less than 10k ohms. In our experiments, to avoid artifacts from electromyography, all the subjects are requested to stabilize their chins and heads on the frame set on the experimental desk and to minimize the movements of their bodies. In this experiment, one trial consists of four sections that provide visual stimuli with different flickering frequencies (8.57 [Hz], 10.00 [Hz], 12.00 [Hz] and 15.00 [Hz]) for the left and right eyes. In the four sections, the left and right flickering frequencies are set as follows: (f_{left},f_{right})= (12.00 [Hz], 10.00 [Hz])) for the first section, and (10.00 [Hz], 8.57 [Hz])), (8.57 [Hz], 15.00 [Hz])), and (15.00 [Hz], 12.00 [Hz])) for the second, third and fourth sections, respectively, where f_{left} and f_{right} denote the flickering frequencies for left-eye stimulus and right-eye stimulus, respectively. Subjects are required to gaze fixedly at the center of the flickering visual stimuli. The flickering time in each section is 12 seconds and then the rest time (without the reversal visual stimuli) is 4 seconds including the short time beep cue (0.5 sec.) and the long time beep cue (1 sec.). The short and long time beep cues are used as the signs of starting and finishing the flickering task, respectively. The time schedule of EEG measurement in each trail is repeated until the required amount of data is collected. In this paper, totally 40 trials (20 trials in Case 1 and 20 trials in Case 2) are carried out for each subject.

III. Algorithm for Perceptual Dominance Estimation in Binocular Rivalry

Section III presents the algorithm for perceptual dominance estimation in binocular rivalry. The algorithm that includes the existing approach [14] as a special case can be employed to verify the hypothesis and the verification will be carried out in Section IV.

Laplacian filtering for the detected EEG data is performed.

$$Y(t) = 4 \times \mathrm{Oz(t)} - (\mathrm{POz(t)} + \mathrm{Iz(t)} + \mathrm{O1(t)} + \mathrm{O2(t)}), \qquad (1)$$

where Oz(t), POz(t), Iz(t), O1(t) and O2(t) denote the EEG data at the electrode places Oz, POz, Iz, O1 and O2 at time t, respectively. Next, the short-time Fourier transform (STFT) of $Y(t)$ is carried out by

$$STFT_Y(t,f) = \int_{-\infty}^{\infty} Y(\tau) w(\tau - t) e^{-j2\pi f/f_s} d\tau, \qquad (2)$$

where f is the frequency index, w is a short time analysis window, and f_s is the sampling rate. The window w is assumed to be non-zero only in an interval of window length. We employ the Hamming window as a window function.

$$w(\tau - t) = \begin{cases} 0.54 - 0.46\cos(2\pi \frac{\tau - t}{L-1}) & 0 \le \tau - t \le L-1, \\ 0 & otherwise, \end{cases}$$

where $L = 3000$ [ms] is the window length. The hamming window with overlap of 2992 [ms] is applied to the EEG data. Note that the sampling rate f_s is 1000[Hz]. Then, since the spectrogram of the function is the magnitude squared of the STFT, the spectrogram is obtained as

$$Power_Y(t, f) = |STFT_Y(t, f)|^2. \tag{3}$$

In [14], perceptual dominance in binocular rivalry was estimated by focusing on difference between $Power_Y(t, f_{\text{right}})$ and $Power_Y(t, f_{\text{left}})$, where f_{left} and f_{right} denote the flickering frequencies for left-eye stimulus and right-eye stimulus, respectively, as defined in Section II. The estimated results are discriminated as right-eye perceptual dominance and left-eye perceptual dominance when

$$\begin{aligned} P_{Ydiff}(t) = Power_Y(t, f_{\text{right}}) - Power_Y(t, f_{\text{left}}) \\ \equiv D^0 P_{Ydiff}(t) \end{aligned} \tag{4}$$

are positive and negative, respectively, where we introduce Euler's notation for $P_{Ydiff}(t)$, that is, we denote the derivative with the operator D. Hence, $D^i P_{Ydiff}(t)$ denotes the i th order differential of $P_{Ydiff}(t)$. This paper will demonstrate that the acceleration of the difference, $D^2 P_{Ydiff}(t)$ (see (6)), is a more important factor than $D^0 P_{Ydiff}(t)$ in the perceptual dominance estimation. The hypothesis verification will be presented and discussed in Section IV. To verify the hypothesis, we introduce an extensive variable (8) defined as the weighted sum of $D^0 P_{Ydiff}(t)$, $D^1 P_{Ydiff}(t)$ and $D^2 P_{Ydiff}(t)$ in Step 5 of the algorithm. For more details, we will discuss it again after describing the algorithm.

Let $BR_{real}(t)$ be the subject's perceptual dominance report based on the feedback from the key press or release task.

$$BR_{real}(t) = \begin{cases} 0 & \text{left-eye visual image perception,} \\ 1 & \text{right-eye visual image perception.} \end{cases} \tag{5}$$

Fig.3 shows the outline of the algorithm for perceptual dominance estimation in binocular rivalry. This algorithm is repeatedly carried out for each 12 second section.

[Algorithm]

[Step1] Calculate (1) and (2) at time t ($t \geq L$). The sampling rate of the calculation in [Step 1] is same as that of EEG measurement. On the other hand, the interval of the calculation during [Step 2]-[Step 5] is same as the interval (8 [msec]) of shifting the Hamming window in the STFT processing.

[Step2] Calculate two spectrograms, $Power_Y(t, f_{\text{left}})$, $Power_Y(t, f_{\text{right}})$, for every interval (8 [msec]).

[Step3] Obtain the difference, $P_{Ydiff}(t)$, in (4).

[Step4] Calculate velocity and acceleration of $P_{Ydiff}(t)$ as

$$D^{i+1} P_{Ydiff}(t) \equiv \frac{\Delta D^i(t)}{\Delta t}, \tag{6}$$

where $\Delta D^i(t) = D^i P_{Ydiff}(t) - D^i P_{Ydiff}(t - \Delta t)$ for $i = 0, 1$ and $\Delta t = 0.008$ [sec.] (i.e., 8 [msec]).

[Step5] Determine $BR_{estimate}(t)$ as

$$BR_{estimate}(t) = \begin{cases} 0 & Switch(t) \leq 0, \\ 1 & Switch(t) > 0, \end{cases} \tag{7}$$

where

$$Switch(t) = \sum_{k=0}^{2} w_{k+1} D^k P_{Ydiff}(t) / D^k_{max}, \tag{8}$$

and $D^k_{max} = max(|D^k P_{Ydiff}(t)|)$, $\forall t$ for $k = 0, 1, 2$. w_1, w_2 and w_3 are the weights that takes between 0 to 1 and $w_1 + w_2 + w_3 = 1$. The $BR_{estimate}(t)$ is the perception result estimated by the algorithm. This is, the estimated results are discriminated as right-eye perceptual dominance and left-eye perceptual dominance when $BR_{estimate}(t) = 1$ and $BR_{estimate}(t) = 0$, respectively

[Step6] If $t < 12 - L$ [sec.] then go to [Step 1]. If $t \geq 12 - L$ [sec.] then the algorithm is finished.

Note that the definition (8) is reduced to the existing approach [14] when $(w_1, w_2, w_3) = (1, 0, 0)$. In addition, $(w_1, w_2, w_3) = (0, 1, 0)$ and $(w_1, w_2, w_3) = (0, 0, 1)$ mean that $D^1 P_{Ydiff}(t)$ and $D^2 P_{Ydiff}(t)$ are considered, respectively. Furthermore, by using weighted parameters (w_1, w_2, w_3), any weighted combinations among them can be considered, e.g., $(w_1, w_2, w_3) = (0.5, 0, 0.5)$ means that both $D^0 P_{Ydiff}(t)$ and $D^2 P_{Ydiff}(t)$ are considered with the same weights, $(w_1, w_2, w_3) = (1/3, 1/3, 1/3)$ means that $D^0 P_{Ydiff}(t)$, $D^1 P_{Ydiff}(t)$ and $D^2 P_{Ydiff}(t)$ are considered with the same weights, and so on. The hypothesis verification is completed if the estimation accuracy by the algorithm with $(w_1, w_2, w_3) = (0, 0, 1)$ is better than those by the algorithm with other weights. From now, we call the algorithm with the weight ($(w_1, w_2, w_3) = (0, 0, 1)$) 'the proposed approach'.

Remark 1: Before calculating a weighted sum of three variables (terms) in (8), all the terms are normalized with the maximum values. Three of them without the normalization should not be simply added since their orders are different. Hence, after normalizing these values (terms) to [-1 1], the weighted sum is calculated.

IV. Evaluation

Section IV verifies the hypothesis by showing that the estimation accuracy by the algorithm with $(w_1, w_2, w_3) = (0, 0, 1)$ is better than those by the algorithm with other weights.

As used in [12], [14], the normalized cross-correlation between $BR_{real}(t)$ and $BR_{estimate}(t)$ is utilized to evaluate the perceptual dominance estimation accuracy in the existing and proposed algorithms. The normalized cross-correlation $R_{xy}(\tau)$ is represented as

$$R_{xy}(\tau) = \frac{C_{xy}(\tau)}{\sqrt{C_{xx}(0) C_{yy}(0)}}, \tag{9}$$

where

$$C_{xy}(\tau) = \lim_{T \to \infty} \int_{-1/T}^{1/T} x(t) y(t + \tau) dt, \tag{10}$$

$x(t) = BR_{estimate}(t)$ and $y(t) = BR_{real}(t)$. The reaction time τ_{act} [12], [14], which is the time delay of the button (key) press from the SSVEP onset, can be defined as the value of τ at the peak of the cross-correlation between a sufficient time range, i.e., $\tau_{min} < \tau < \tau_{max}$ [msec.]. The maximum value of

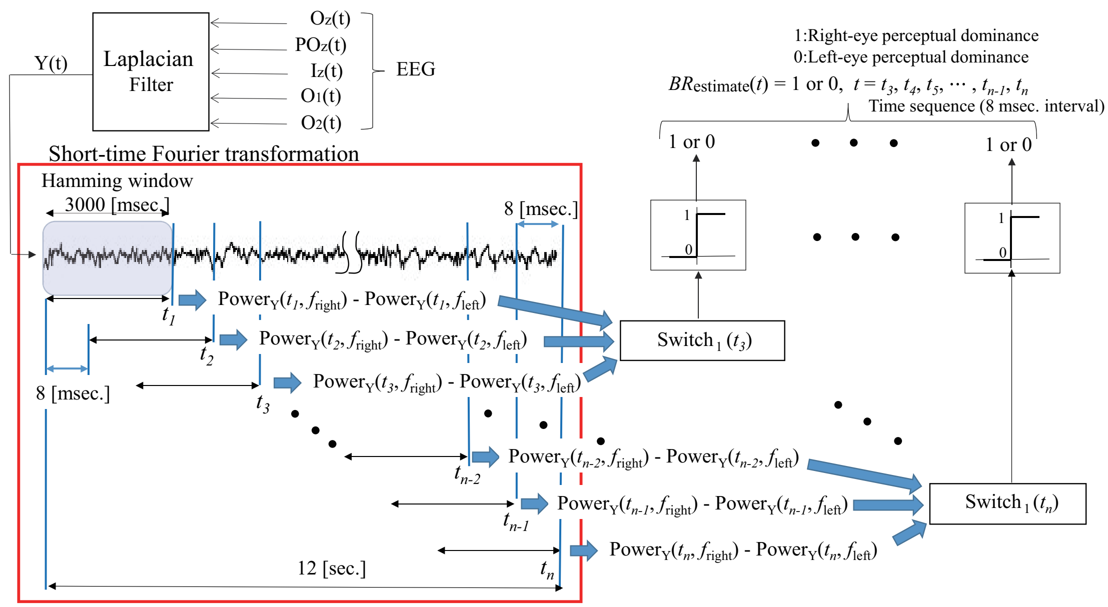

Fig. 3. Outline of algorithm for perceptual dominance estimation.

R_{xy}, defined by R_{max}, at the reaction time τ_{act} is utilized to evaluate the perceptual dominance estimation accuracy, i.e.,

$$R_{\max} = \max_{\tau_{min}<\tau<\tau_{max}} R_{xy}(\tau). \tag{11}$$

R_{max} is calculated for each 12 second section. We evaluate each estimation result at each 12 second section with R_{max} and calculate the average and standard deviation of R_{max} for all the 12 second sections as the final evaluation. Figs. 4 and 5 show the plot of the average of ten subjects' R_{max} on the region (w_1, w_3) (under the restriction $w_1 + w_2 + w_3 = 1$) in Case 1 and Case 2, respectively, where $\tau_{min} = 0$ and $\tau_{max} = 900$ that are the same setting as in [14]. Points A, B and C correspond to $(w_1, w_2, w_3) = (1, 0, 0)$, $(w_1, w_2, w_3) = (0, 0, 1)$, $(w_1, w_2, w_3) = (0, 1, 0)$, respectively. In both Case 1 and Case 2, R_{max} at Point B is larger than that at Point C, and R_{max} at Point C is larger than that at Point A. The results indicate that $D^2P_{Ydiff}(t)$ is a more important factor than $D^0P_{Ydiff}(t)$ in the perceptual dominance estimation. $D^1P_{Ydiff}(t)$ seems to be also an important fact. However, in all the combinations (8) with the constraint $w_1+w_2+w_3 = 1$, Point B in both Figs. 4 and 5 are the largest point of R_{max}. R_{max} increases gradually when w_3 tend to 1, that is, when it is approaching to Point B. This results strongly support the utility of the proposed approach.

Tables I and II show the averages and standard deviations of R_{max} in the proposed approach and the existing approach for Cases 1 and 2, respectively. In both Cases 1 and 2, the estimation accuracies in the proposed approach are significantly improved over those in the existing approach. Furthermore, the standard deviations of R_{max} in the proposed approach are much smaller than those in the existing approach. This means that the proposed algorithm provides better estimation results for almost all EEG data. Thus, the proposed approach provides better results than the existing approach. As the t-test results for R_{max} between the proposed approach and the

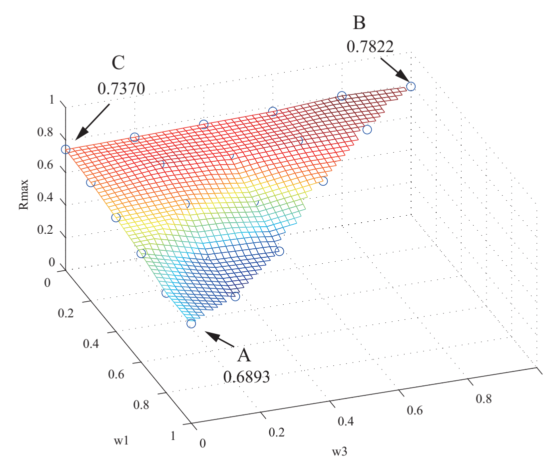

Fig. 4. 3D plot of R_{xy} on the region (w_1, w_3) (Case 1).

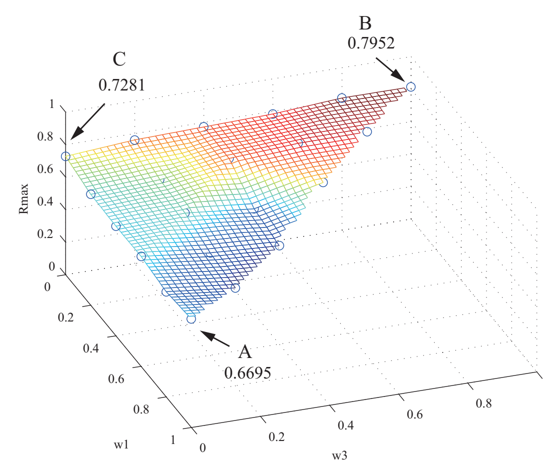

Fig. 5. 3D plot of R_{xy} on the region (w_1, w_3) (Case 2).

TABLE I
AVERAGES AND STANDARD DEVIATIONS OF R_{max} FOR CASE 1.

Subject	Existing Approach [14]	Proposed Approach
A	0.7002 $\pm$ 0.2567	0.8028 $\pm$ 0.1434
B	0.6038 $\pm$ 0.3192	0.7907 $\pm$ 0.2093
C	0.7201 $\pm$ 0.2948	0.8031 $\pm$ 0.1573
D	0.7339 $\pm$ 0.2518	0.8206 $\pm$ 0.1058
E	0.6869 $\pm$ 0.2550	0.7052 $\pm$ 0.2150
F	0.6972 $\pm$ 0.2638	0.7615 $\pm$ 0.2134
G	0.7415 $\pm$ 0.2552	0.7355 $\pm$ 0.1208
H	0.7081 $\pm$ 0.2785	0.7801 $\pm$ 0.1731
I	0.6785 $\pm$ 0.2822	0.8277 $\pm$ 0.1314
J	0.6233 $\pm$ 0.3219	0.7952 $\pm$ 0.2012
Ave.	0.6893 $\pm$ 0.2779	0.7822 $\pm$ 0.1671

TABLE II
AVERAGES AND STANDARD DEVIATIONS OF R_{max} FOR CASE 2.

Subject	Existing Approach [14]	Proposed Approach
A	0.6405 $\pm$ 0.2976	0.7932 $\pm$ 0.1619
B	0.5459 $\pm$ 0.3800	0.8360 $\pm$ 0.1492
C	0.7706 $\pm$ 0.2362	0.8199 $\pm$ 0.1437
D	0.6710 $\pm$ 0.2787	0.7896 $\pm$ 0.1591
E	0.6453 $\pm$ 0.3118	0.7805 $\pm$ 0.1964
F	0.7413 $\pm$ 0.2727	0.8476 $\pm$ 0.1597
G	0.6619 $\pm$ 0.3005	0.6862 $\pm$ 0.2012
H	0.6291 $\pm$ 0.3261	0.8159 $\pm$ 0.1842
I	0.5958 $\pm$ 0.2843	0.7731 $\pm$ 0.1432
J	0.7938 $\pm$ 0.3376	0.8096 $\pm$ 0.1361
Ave.	0.6695 $\pm$ 0.3025	0.7952 $\pm$ 0.1635

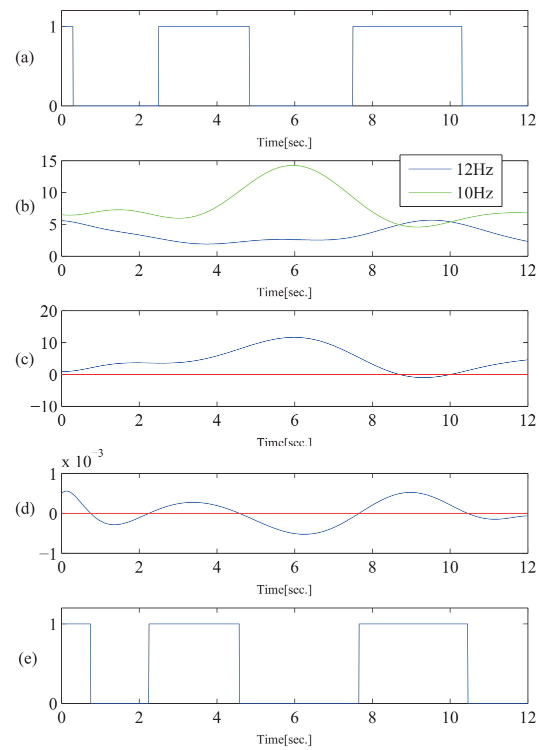

Fig. 6. Plots of BR_{real} and $BR_{estimate}$ for a section of (f_{left},f_{right})= (12.00 [Hz], 10.00 [Hz])) in Case 1 of Subject A:(a) $BR_{real}(t)$, (b) $Power_Y(t, f_{\text{left}})$ and $Power_Y(t, f_{\text{right}})$, (c) $D^0P_{Y\,diff}(t)$, (d) $D^2P_{Y\,diff}(t)$, (e) $BR_{estimate}(t)$.

existing approach in Tables I and II, the p-values are obtained as $p < 0.05$. The p-values are small ($p < 0.05$) in both Cases 1 and 2. This means that there is enough evidence to reject the null hypothesis at the 5% significance level, that is, it is concluded that there is enough evidence that the proposed approach is better than the existing approach. Thus, by introducing $D^2P_{Y\,diff}(t)$, the estimation results can be significantly enhanced in both Cases 1 and 2. As for difference between Case 1 and Case 2, as a result of the t-test, the p-values associated with the t-test between Case 1 and Case 2 are not small ($p > 0.05$) in both the existing and proposed approaches. Hence, the t-test result does not allow to point out the effect of the colored pattern stimuli for the estimation results in this experiment. Fig. 6 shows plots of the BR_{real} and the $BR_{estimate}$ for a section of (f_{left},f_{right})= (12.00 [Hz], 10.00 [Hz])) in Case 1 of Subject A. The estimation result $BR_{estimate}$ agrees well with the feedback report BR_{real}.

The flickering nature of the stimulus, as well as other features (like frequency, pattern or brightness [30]), could affect the way in which perceptual dominance/binocular rivalry occurs in the brain. This will also need to be investigated in future work.

V. CONCLUSION

This paper has presented a practical SSVEP-based algorithm for perceptual dominance estimation in binocular rivalry from EEG signals. The algorithm is real-time and effective and has significantly improved accuracy over the existing approach. For accuracy of estimation, the algorithm has utilized the spectrogram obtained by the short-time Fourier transformation with a short time analysis window. More importantly, the algorithm has focused on the acceleration of the spectrogram difference between SSVEP of left-eye stimulus and that of right-eye stimulus. The experimental results have demonstrated the utility and applicability of the algorithm, and in particular, the importance of introducing the acceleration of the spectrogram difference. Since the algorithm is quite simple and fast, e.g., it is possible to work in 8 [ms] sampling rate, it is indeed suitable to accurately measure binocular rivalry without verbal communications in real-time environments.

One of our future works is to investigate the reasons why the acceleration information contributes to better results from the physiological mechanism points of view. Moreover, we will explore the possibility of its application to animals.

ACKNOWLEDGMENT

The authors would like to thank Mr. Tomohiro Goto, the University of Electro-Communications, for his support of the experiments in this research.

REFERENCES

[1] C. Wheatstone, “Contributions to the physiology of vision. Part the First. On some remarkable, and hitherto unobserved, phenomena of binocular vision,” Philosophical Transactions of the Royal Society of London, Vol.128, pp.371-394, June 1838.

[2] H. von Helmholtz, Handbuch der physiologishen Optik, 3rd edn (Vol. 3), Hamburg: Leopold Voss. Hamburg, 1910.

[3] A. Bartels; N. K. Logothetis, “Binocular rivalry: A time dependence of eye and stimulus contributions,” Journal of Vision, vol.10, no.12, pp.1-14, October 2010.

[4] R. Blake and N. K. Logothetis, “Visual competition,” Nature Reviews Neuroscience 3, 13-21, January 2002.
[5] D. Carmel, M. Arcaro, S. Kastner and U. Hasson, “How to Create and Use Binocular Rivalry,” Journal of Visualized Experiments, Vol.45, No.1, pp.1-8, Nov. 2010.
[6] P. Zhang, K. Jamison, S. Engel, B. He, and S. He, “Binocular Rivalry Requires Visual Attention,” Neuron 71 (2), pp.362-369, July 2011.
[7] F. Vialattea, M. Mauriceb, J. Dauwelsc and A. Cichockia, “Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives,” Progress in Neurobiology, Vol.90, No. 4, pp.418-438, April 2010.
[8] J. W. Brascamp, P.C. Klink, “The ‘ laws ’ of binocular rivalry: 50 years of Levelt ’s propositions,” Vision Research, Vol. 109, Part A, pp.20-37, April 2015.
[9] S. Katyal, S. A. Engel, B. He, S. He, “Neurons that detect interocular conflict during binocular rivalry revealed with EEG,” Journal of Vision, Vol.16, No.3, pp.1-12, Feb. 2016.
[10] T. Kobayashi, K. Akamatsu and H. Natsukawa, “Cortical Neural Activities Associated with Binocular Rivalry: An EEG-fMRI Integrative Study,” 35th Annual International Conference of the IEEE EMBS Osaka, Japan, July, 2013, pp. 3-7.
[11] T. Yamazoe, S. Kishi, T. Shibata, T. Kawai, and M. Otsuki “Reducing Binocular Rivalry in the Use of Monocular Head-Mounted Display,” JOURNAL OF DISPLAY TECHNOLOGY, Vol. 3, No. 1, pp.83-88, March 2007.
[12] R. J. Brown and A. M. Norcia, “ A method for investigating binocular rivalry in real-time with the steady-state VEP,” Vision Research, 2701-2708, 1997.
[13] W. Einhäuser, J. Stout, C. Koch, O. Carter, “ Pupil dilation reflects perceptual selection and predicts subsequent stability in perceptual rivalry,” Proceedings of the National Academy of Sciences of the United States of America,Vol.105, No.5, pp.1704-1709, Feb. 2008.
[14] R. Wang, X. Gao, S. Gao, “A Study on Binocular Rivalry Based on the Steady State VEP,” Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, 256-259, 2004.
[15] P. Stawicki, F. Gembler, I. Volosyak, “Evaluation of Suitable Frequency Differences in SSVEP-Based BCIs,” Volume 9359 of the series Lecture Notes in Computer Science, pp 159-165, Springer, 2015.
[16] D. Marr, “Vision:A Computational Investigation into the Human Representation and Processing of Visual Information,” MIT Press, 1982.
[17] E. H. Adelson and J. R. Bergen, “Spatiotemporal energy models for the perception motion,” Journal of the Optical Society of America A, Vol.2, No.2, pp.284-299, Feb. 1985.
[18] R. L. De Valois and N. P. Cottaris, “Inputs to directionally selective simple cells in macaque striate cortex,” Proceedings of the National Academy of Sciences, Vol. 95, pp. 14488-14493, November 1998.
[19] G. C. DeAngelis, I. Ohzawa, and R. D. Freeman, “Spatiotemporal Organization of simple-cell receptive fields in the cat’s striate cortex. I. General Characteristics and postnatal development,” Journal of Neurophysiology, vol. 69, no.4, pp.1091-1117, April 1993.
[20] K. L. Challinor and G. Mather, “A motion-energy model predicts the direction discrimination and MAE duration of two-stroke apparent motion at high and low retinal illuminance,” Vision Research, Vol.50, No.12, pp.1109-1116, 2010.
[21] A. Pavan, A. Contillo, G. Mather, “Modelling fast forms of visual neural plasticity using a modified second-order motion energy model,” J. Comput Neurosci, vol.37, no.3, pp.493-504, December 2014.
[22] S. Nishimoto, An T. Vu, T. Naselaris, Y. Benjamini, B. Yu, and J. L. Gallant, “Reconstructing Visual Experiences from Brain Activity Evoked by Natural Movies, Current Biology,” Vol. 21, Issue 19, pp.1641-1646, October 2011.
[23] N. Giles, H. Lau, and B. Odegaard1, “What Type of Awareness Does Binocular Rivalry Assess?,” Trends in Cognitive Sciences, Vol. 20, No. 10, pp.719-720, October 2016.
[24] D. L. Sheinberg and N. K. Logothetis, “The role of temporal cortical areas in perceptual organization,” Proceedings of the National Academy of Sciences of the United States of America,Vol. 94, pp. 3408-3413, April 1997.
[25] D. A. Leopold, N. K. Logothetis, “Activity changes in early visual cortex reflect monkeys’ percepts during binocular rivalry,” Nature, 379(6565), pp.549-553, Feb. 1996.
[26] R. E. Crist and M. A. Lebedev, “Methods for Neural Ensemble Recordings (Editor:N. MAL, 2nd edition), Chapter 9 Multielectrode Recording in Behaving Monkeys,” CRC Press/Taylor & Francis, 2008.
[27] R. D. Glickman, J. W. Rhodes, D. J. Coffey, “Noninvasive techniques for assessing the effect of environmental stressors on visual function,” Neuroscience & Biobehavioral Reviews, Vol. 15, No. 1, pp. 173-178, Spring 1991.
[28] P. E. Williams, F. Mechler, J. Gordon, R. Shapley1, M. J. Hawken, “Entrainment to Video Displays in Primary Visual Cortex of Macaque and Humans,” The Journal of Neuroscience, 24(38), pp. 8278-8288, September 2004
[29] P. D. Butler, Y. Chen, J. M. Ford, M. A. Geyer, S. M. Silverstein, and M. F. Green, “Perceptual Measurement in Schizophrenia: Promising Electrophysiology and Neuroimaging Paradigms From CNTRICS,” Schizophrenia Bulletin, Vol.38 No.1, pp.81-91, Jan 2012.
[30] D. Zhu, J. Bieger, G. G. Molina, R. M. Aarts, “A Survey of Stimulation Methods Used in SSVEP-Based BCIs,” A Computational Intelligence and Neuroscience, Vol.2010, No.1, pp.1-13, January 2010. .
[31] H. H. Japer, “The ten-twenty electrode system of the international federation in electroencephalography and clinical neurophysiology,” Electroencephalgr. Clin. Neurophysiol., Vol.10, pp.371-375, 1958.

Kazuo Tanaka (S’87 - M’91 - SM’09 - F’14) received the B.S. and M.S. degrees in Electrical Engineering from Hosei University, Tokyo, Japan, in 1985 and 1987, and Ph.D. degree, in Systems Science from Tokyo Institute of Technology, in 1990, respectively.

He is currently a Professor in Department of Mechanical and Intelligent Systems Engineering at The University of Electro-Communications. He was a Visiting Scientist in Computer Science at the University of North Carolina at Chapel Hill in 1992 and 1993. He received the Best Young Researchers Award from the Japan Society for Fuzzy Theory and Systems in 1990, the Outstanding Papers Award at the 1990 Annual NAFIPS Meeting in Toronto, Canada, in 1990, the Outstanding Papers Award at the Joint Hungarian-Japanese Symposium on Fuzzy Systems and Applications in Budapest, Hungary, in 1991, the Best Young Researchers Award from the Japan Society for Mechanical Engineers in 1994, the Outstanding Book Awards from the Japan Society for Fuzzy Theory and Systems in 1995, 1999 IFAC World Congress Best Poster Paper Prize in 1999, 2000 IEEE Transactions on Fuzzy Systems Outstanding Paper Award in 2000, the Best Paper Selection at 2005 American Control Conference in Portland, USA, in 2005, the Best Paper Award at 2013 IEEE International Conference on Control System, Computing and Engineering in Penang, Malaysia, in 2013, the Best Paper Finalist at 2013 International Conference on Fuzzy Theory and Its Applications, Taipei, Taiwan in 2013, the Best Poster Award at First International Symposium on Swarm Behavior and Bio-Inspired Robotics (SWARM2015), Kyoto, Japan, in 2015. His research interests include intelligent systems and control, nonlinear systems control, robotics, brain-machine interface and their applications. He co-authored (with Hua O. Wang) the book Fuzzy Control Systems Design and Analysis: A Linear Matrix Inequality Approach (Wiley-Interscience, 2001).

He has served as an Associate Editor for Automatica and for the IEEE Transactions on Fuzzy Systems, and is on the IEEE Control Systems Society Conference Editorial Board. He is a fellow of IEEE and IFSA.

Motoyasu Tanaka (S’05 - M’12) received his B.S., M.S., and Ph.D. degrees in Engineering from the Department of Mechanical Engineering and Intelligent Systems at the University of Electro-Communications, Japan in 2005, 2007, and 2009, respectively. From 2009 to 2012, he worked at Canon, Inc., Tokyo, Japan. He is currently an Associate Professor in the Department of Mechanical and Intelligent Systems Engineering at the University of Electro-Communications. His research interests include biologically inspired robotics and dynamics-based nonlinear control. He received the IEEE Robotics and Automation Society Japan Chapter Young Award from the IEEE Robotics and Automation Society Japan Chapter in 2006, and the Best Poster Award at SWARM2015: The First International Symposium on Swarm Behavior and Bio-Inspired Robotics in 2015.

Toshiya Kajiwara received the B.S. in Mechanical Engineering and Intelligent Systems and M.S degree in Human Media Systems from the University of Electro-Communications, Tokyo, Japan, in 2013 and 2015 respectively. His research interests include brain machine interface and its applications.

Hua O. Wang (M'94-SM'01) received the B.S. degree from the University of Science and Technology of China (USTC), Hefei, China, in 1987, the M.S. degree from the University of Kentucky, Lexington, KY, in 1989, and the Ph.D. degree from the University of Maryland, College Park, MD, in 1993, all in Electrical Engineering.

He has been with Boston University where he is currently an Associate Professor of Aerospace and Mechanical Engineering since September 2002. He was with the United Technologies Research Center, East Hartford, CT, from 1993 to 1996, and was a faculty member in the Department of Electrical and Computer Engineering at Duke University, Durham, NC, from 1996 to 2002. Dr. Wang served as the Program Manager (IPA) for Systems and Control with the U.S. Army Research Office (ARO) from August 2000 to August 2002. During 2000 - 2005, he also held the position of Cheung Kong Chair Professor and Director with the Center for Nonlinear and Complex Systems at Huazhong University of Science and Technology, Wuhan, China.

Dr. Wang is a recipient of the 1994 O. Hugo Schuck Best Paper Award of the American Automatic Control Council, the 14th IFAC World Congress Poster Paper Prize, the 2000 IEEE Transactions on Fuzzy Systems Outstanding Paper Award, the Best Paper Award at 2013 IEEE International Conference on Control System, Computing and Engineering. His research interests include control of nonlinear dynamics, intelligent systems and control, networked control systems, robotics, cooperative control, and applications. He co-authored (with Kazuo Tanaka) the book Fuzzy Control Systems Design and Analysis: A Linear Matrix Inequality Approach (Wiley-Interscience, 2001). Dr. Wang has served as an Associate Editor for the IEEE Transactions on Automatic Control and was on the IEEE Control Systems Society Conference Editorial Board. He is an Editor for the Journal of Systems Science and Complexity. He is an appointed member of the 2006 Board of Governors of the IEEE Control Systems Society and a senior member of IEEE.