Mental Focus Analysis Using the Spatio-temporal Correlation between Visual Saliency and Eye Movements

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Abstract: The spatio-temporal correlation analysis between visual saliency and eye movements is presented for the estimation of the mental focus toward videos. We extract spatio-temporal dynamics patterns of saliency areas from the videos, which we refer to as saliency-dynamics patterns, and evaluate eye movements based on their correlation with the saliency-dynamics patterns in view. Experimental results using TV commercials demonstrate the effectiveness of the proposed method for the mental-focus estimation.

Keywords: mental focus, spatio-temporal analysis, saliency map, eye movement

1. Introduction

Understanding mental states of users, who face interactive display systems to browse various kinds of information, allows building a smooth interaction between users and systems. Our goal is to estimate the mental focus of users from their eye movements, which indicates whether they pay attention to a specific task. Especially in this paper, we focus on the estimation of the mental focus while users watch general videos such as TV commercials; that is, we consider the mental focus as the strength of users’ attention toward videos, and besides, we assume the strength can be quantified into several levels (e.g., high and low).

Eyes are a window into the mind; eye movements are often regarded as one of the crucial clues to estimate user states such as the attention[1],[2],[3]. Analysis of the eye movements includes eye blinks[1], PERCLOS (PERcentage of eyelid CLOSure)[4], or their combination using Bayesian networks[5]. The basic concept behind these studies is that eye movements can be affected by the user states as well as contents being looked at. And there the analysis of relationships between contents and eye movements plays a key role. Existing work can be characterized by what kind of relationships the method uses. For example, many studies on interactive systems basically begin the analysis by specifying objects being looked at, and then extract the features such as the gaze duration[6], 3-gram sequence of gaze targets[7], or the reaction time to dynamic content updates[8]. In order to obtain the detailed psycho-cognitive processes, the consideration of content semantics is furthermore required[9]. Some works on driving assistance systems investigate the correlation between eye gazes and surrounding environments. They look for salient objects from surrounding environments using optical flow[2] or obstacle, sign and pedestrian detection[3], and analyze the relationship between gaze directions and the object positions to estimate the drivers attention.

Those related works basically specify gaze-related objects or their semantic relationships based on some heuristics about contents or surrounding environments in advance. However, because general videos contain enormous kinds of objects, it is difficult to specify all the objects and their relationships using the heuristics applied in the related works. Besides, eye movements have a large variety of dynamics caused by contents and users’ states. Therefore, the analysis of eye movements detailed enough to realize the mental-state estimation essentially requires (1) the spatial structure that describes gaze targets and the other surrounding objects in view, and (2) the temporal structure of dynamics between both eye movements and the targets.

In this paper, we propose a novel method for the mental-focus analysis that utilizes the spatio-temporal relationship of dynamics in both objects and eye movements. The main contribution is to introduce an analysis of eye-movement dynamics by categorizing them from the aspect of objects’ dynamics in view. This enables us to switch an appropriate feature set of eye movements according to objects’ dynamics, and is expected to enhance the accuracy of the estimation of mental focus. In order to analyze dynamics in displayed contents without using specific semantic heuristics, we employ the saliency map[10], which is known as a model of a visual attention system. With consideration of the influence on eye movements, we classify the dynamics of extracted saliency areas into several patterns called saliency-dynamics patterns, which specify corresponding eye movements and their features. Thus, once a saliency-dynamics pattern is identified from contents data in a certain time window, we can evaluate the eye movements to estimate the level of the mental focus.

The overview of our proposed analysis is as follows. As shown in Fig. 1 (a), we first extract the spatio-temporal saliency volumes S referred to as saliency flows. S are regarded as the candidates

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2. Video Saliency Extraction and Analysis

2.1 Visual Saliency in a Video

Videos have visual saliency areas which attract human eye gazes. We employ the saliency map [10] to obtain the saliency areas in a video, and utilize the areas as objects to be looked at. The saliency map is a bottom-up computational model of visual attention, which typically includes the extraction of multiple low-level visual features such as the intensity, the color, the orientation from an image at multiple scales, normalization and integration of features into a 2D map with a saliency value at each pixel.

Studies on visual-attention systems such as the saliency map basically aim to evaluate their model by predicting human gaze behaviors [11], [12], with no consideration of mental states. On the other hand, the proposed method aims to analyze the relationship between gaze behaviors and the obtained saliency map, in order to estimate the mental focus.

We extract saliency areas from a video; a saliency map $\hat{\iota}_t$ is computed from an input frame $\iota_t$ at the time $t$ and each pixel $c \in N^2$ is given a saliency value $\hat{\iota}_t(c)$. $\hat{\iota}_t$ is thresholded at $\pi_s$ and the remaining pixels are segmented into a set of saliency areas $S_t = \{s_{t,1}, \ldots, s_{t,N_t}\}$ by 8-connectivity labeling (see Fig. 2 (a)).

2.2 Saliency Flow Construction

As mentioned in Section 1, the spatio-temporal saliency dynamics is utilized for eye-movement analysis. So we extend the visual saliency into spatio-temporal volumes referred to as saliency flows (see Fig. 2 (b)). The saliency flows are defined as simply-connected 3D volumes composed by temporally-continuous saliency areas, and they contain the time-varying pat-
tern of their shape, position, and saliency value. Videos are often expected to contain several flows, so we assign an ID to each constructed flow. The following procedure gives an ID \( l_{(a)} \) to a saliency area \( s_{(a,t)} \) so that we bundle a set of saliency areas into a single flow.

For the area \( s_{(a,t)} \), we look for a set of area \( \hat{S}_{t-1} \) from \( S_{t-1} \), the elements of which are spatio-temporally continuous to \( s_{(a,t)} \). Since saliency flows are defined as simply-connected, branches in the flows should be avoided. Such branches are formed where multiple areas are connected to \( s_{(a,t)} \), so we assign \( l_{(a)} \) based on the number of elements in \( \hat{S}_{t-1} \) (denoted as \( \text{Card}(\hat{S}_{t-1}) \)); the cardinality of \( \hat{S}_{t-1} \):

(a) If \( \text{Card}(\hat{S}_{t-1}) = 0 \); no area can be found in \( \hat{S}_{t-1} \), \( s_{(a,t)} \) consists of the saliency flow which emerges at \( t \). Then a new ID number is given to \( l_{(a,t)} \).

(b) If \( \text{Card}(\hat{S}_{t-1}) = 1 \); a single area can be found in \( \hat{S}_{t-1} \), \( s_{(a,t)} \) is the following area to \( s_{(a-1,t)} \) in \( \hat{S}_{t-1} \). This case \( l_{(a)} \) receives the ID \( l_{(1-a)} \).

(c) If \( \text{Card}(\hat{S}_{t-1}) \geq 2 \); more than one area can be found in \( \hat{S}_{t-1} \), \( s_{(a,t)} \) is the area with the collision of multiple flows. For this case \( l_{(a)} \) receives the ID \( l_{(1-a,b)} \) of area \( s_{(a-1,b)} \) in \( \hat{S}_{t-1} \) which locates the nearest position to \( s_{(a,t)} \).

Once \( l_{(a)} \) is assigned, we look for areas which have the same ID number in \( S_t = \{s_{(1,1)}, \ldots, s_{(n,t)}\} \). If any area exists, \( s_{(a,t)} \) is one of the branches which emerges at \( t \). In this case \( l_{(a,t)} \) is relabeled to a new ID number.

Let us assume that the maximum ID \( L \) is given by the above procedure, and the ID \( l_{(a,t)} \in \{1, \ldots, L\} \) is defined for the area \( s_{(a,t)} \). Besides, let us define here the function that returns the ID from a single pixel \( e \) at the time \( t \) as

\[
\text{SID}_t(e) = l \ (l \in \{1, \ldots, L, \zeta\}),
\]

where \( \zeta \) denotes the state in which no flow exists at \( e \). A saliency flow labeled as \( l \) is composed by a set of saliency areas \( S_l^{(t)} \equiv \{s_{(a,t)} \mid l_{(a,t)} = l\} \). This flow exists in the temporal interval \([b_l, e_l] \), and the area covered with \( S_l^{(t)} \) at the time \( t \) is represented as \( \hat{S}_{l}^{(t)} \).

### 2.3 Saliency Dynamics Analysis

A set of saliency flows \( S = \{S^{(1)}, \ldots, S^{(L)}\} \) represents the saliency dynamics. Each element of \( S \), a saliency flow \( S^{(t)} \), contains the time varying pattern of its shape, position and saliency value. Above all, a motion is well known as one of the important features to enhance the saliency [14]. The motion is therefore expected to affect an attractiveness of saliency flows, and it is also expected to affect eye-movement dynamics; the saliency flows with or without motion cause different types of the eye movements (see Section 3 for details).

So we extract motion features of saliency flows, and classify motion patterns of saliency dynamics using their motion features for eye-movement analysis. The flow position \( c^{(t)} \) using the centroid of \( S^{(t)} \) is defined as follows:

\[
e^{(t)} = \frac{1}{\text{Card}(S^{(t)})} \sum_{s \in S^{(t)}} e.
\]

A position sequence \( C^{(t)} = \{c^{(t)} \mid t \in [b_t, e_t]\} \) is obtained from \( S^{(t)} \).
3. Eye Movements Analysis Using Saliency Dynamics

3.1 Mental Focus and Eye Movements

Mental focus is here defined as a state that specifies whether humans pay attention to video viewing tasks, and we assume the state can be quantified into several levels. Kahneman proposed the attention theory that likens attention to a limited resource which is allocated to tasks [15]. Following this theory, the level of the mental focus can be regarded as the amount of attention resource that allocates to the tasks. Besides, human information processing can be classified into two types [16]: controlled processing is driven by human intentions, and automatic processing is on the other hand a passive outcome of visual stimuli. We define the eye movements in a controlled mode as endogenous eye movements, and in an automatic mode as exogenous eye movements.

Based on these two theories, we assume the following mental focus and eye movements relationship model. From mental factors such as intentions or physiological factors such as fatigues, the level of mental focus is determined and attention resource is allocated. This attention resource causes endogenous eye movements, and some visual stimuli in saliency dynamics cause exogenous eye movements as well. Eye gaze data is observed by mixing these eye movements.

Eye movements have different features according to their type, and therefore have to be evaluated in a different way. The first step toward the estimation is to classify the eye-movement type using saliency dynamics. After that we extract features from the eye movements differently according to their type.

3.2 Eye Movements in Video Viewing

We summarize the kinds of eye movements being observable on a screen, which take place during video viewing, so that we can classify them (see Fig. 4). When we humans watch videos, iterative scanning and selection of objects are expected to be observed. Here, we employ the following primitive eye movements from a biomedical research [17]: saccade, fixation and smooth pursuit, and try to describe characteristics of the scanning and the selection of objects are expected to be observed.

The scanning movements present steady behaviors, and therefore have to be evaluated in a different way. The first step toward the estimation is to classify the eye-movement type using saliency dynamics. After that we extract features from the eye movements differently according to their type.

Fixation scan (FS) is a scanning eye movement of static saliency flows. FSs can be described as the combination of fixations: maintenance of gaze on a single location, and saccades: rapid and jerky gaze shifts.

Pursuit scan (PS) is a scanning of moving (dynamic) saliency flows. PSs contain smooth pursuits of the flow motions, and saccades.

On the other hand, the selection movements present transitional behaviors, and are caused voluntarily as well as by visual stimuli in saliency flows. Therefore, they can be classified based on the type of human information processing. We introduce the term events that represent visual stimuli in the flows. Events are defined here as emergences or mode transitions from static to dynamic. They cause exogenous gaze shifts, and according to the their association with target selections, the following eye movements are introduced:

Endogenous target change (NC) is a gaze shift between saliency flows that occurs asynchronously with events.

Using NCs, humans voluntarily determine which flows to scan next, and manage to shift their gaze.

Exogenous target change (XC) is also a gaze shift between saliency flows but it occurs in synchronization with events in a destination flow. The feature of XCs is that humans do not consciously shift their gaze.

3.3 Eye Movements Classification

Let us assume that eye-gaze data \( x_t \in \mathbb{R}^2 \), a 2D point on a screen is obtained using an eye tracker. The four eye movements mentioned above are specified from the observed sequence of eye-gaze points \( X = (x_1, x_2, \ldots) \) (see Fig. 5).

Segmentation

For the classification, we first produce intervals \( < g_k, \tau_k > \) from \( X \), each of which has a single target flow with ID \( g_k \) and duration \( \tau_k \). By following Eq. (1), the reference from a point \( x_t \) to a flow ID is described as follows:

\[
g(t) = S|D|e(x_t) \in \{1, \ldots, L, \zeta, \eta\}. \quad (3)
\]

Notice that the numbers \( 1, \ldots, L \) denote the flow IDs, \( \zeta \) shows that no flow locates at the point, and \( \eta \) shows that the human blinks or looks outside of a screen. Using target-flow changes, we obtain a target-flow sequence with duration \( G = (g_1, \tau_1, \ldots, g_K, \tau_K) \), which consists of \( g_k \notin [\zeta, \eta] \) (see Fig. 5 (a)). We then divide \( g_k, \tau_k \) based on mode transitions in the flow \( S^{(k)} \), \( \tau_k > \) is divided into \( (m_1, \tau_1 ), (m_2, \tau_2 ), \ldots, (m_{k-1}, \tau_{k-1}) \) by a set of mode-transition time in \( S^{(k)} \). After the division, we renew subindices to get a sequence of target-flow mode with duration:

\[
G' = (m_1, \tau_1 ), (m_2, \tau_2 ), \ldots (m_{K'}, \tau_{K'}) \quad (see \ Fig. 5 \ (b)).
\]

Classification

We classify the eye movements using the obtained mode sequence \( G' \). Let us assume that \( < m_k, \tau_k > \) exists in the interval \([b_k, e_k] \). We describe a sequence of eye-gaze points in \( < m_k, \tau_k > \) as \( X^{(k)} = \{ x_t \mid t \in [b_k, e_k] \} \) and of eye-gaze points between \( < m_{k-1}, \tau_{k-1} > \) and \( < m_k, \tau_k > \) as \( X^{(k-1,k)} = \{ x_t \mid t \in [b_{k-1}, b_k] \} \), which will individually correspond to specific eye movements.
FSs and PSs take place within the interval \(< m_k, \tau'_{k}\) and \(X^{(k)}\) can be classified to either of them. These eye movements can be classified using modes of their gaze targets; based on the target-flow mode \(m_k\), we assign the label FS to \(X^{(k)}\) if \(m_k = m_s\) and PS if \(m_k = m_d\).

On the other hand, NCs and XCs take place between two intervals \(< m_{k-1}, \tau'_{k-1}\) and \(< m_k, \tau'_{k}\). As mentioned in Section 3.2, these two movements are discriminated by observing whether the eye movement is synchronized with events or not. Specifically, we evaluate the temporal distance between the starting time of the eye movements and that of the corresponding events to discriminate the two movements. Let us assume that the most recent event from \(b_k\) occurs at \(T_k^{(b_k)}\) in NC/XC destination flows. NCs are then discriminated from XCs using temporal distance between \(T_k\) and \(b_k\); if \(b_k - T_k\) is within the reaction time \(\sigma\) of exogenous saccades (generally around 0.2 sec [18]), \(X^{(k-1)}\) can be labeled as XC, and otherwise it is labeled as NC. Finally we obtain the sequence of eye movements, \(X^{(1)}, X^{(1,2)}, X^{(2)}, \ldots, X^{(K-1)}, X^{(K)}\), labeled by FS, PS, NC, or XC (see Fig. 5 (c)).

4. Mental Focus Estimation

4.1 Estimation Overview

Following the procedure in Section 3, a sequence of eye movements, consisting of fixation scan FS, pursuit scan PS, endogenous target change NC and exogenous target change XC, is obtained. This section presents the feature extraction of the eye movements and the estimation of the mental focus. We assume that the level of mental focus corresponds to the amount of attention resource to tasks, and that humans scan or select saliency flows more actively using the resource when they are in a higher level of mental focus.

Eye movements have different characteristics according to their type, and thus we first extract features which indicate activities in video viewing, from the observed eye movements in a different way for their type. Since we focus on dynamic aspects in eye movements, the features are extracted as summaries of their dynamics. Here, the eye movements are affected not only by a target flow but by the other surrounding flows in a scene. For instance, scenes composed of multiple flows cause NC and XC whereas scenes with a single flow cause only FS or PS. In addition, when the scene includes both static and dynamic flows, PS seems to be observed more often than FS because the dynamic flows are more salient than the static ones. That is, the features can perform differently according to the type of saliency-dynamics patterns, which indicate the number and modes of existing flows.

Therefore, we then integrate the features, which are extracted from the eye movements in a certain time window defined by the saliency-dynamics patterns, into a feature set. The observable eye movements for each of the patterns can be derived as Table 2, since the eye movements are categorized by their association with modes or events of saliency flows. By learning a discriminative model from the feature sets for each pattern, we can estimate the level of mental focus by switching an appropriate model to the observed eye movements based on the corresponding saliency-dynamics patterns in view.

4.2 Feature Extraction

As shown in Section 3.2, FSs and PSs are steady eye movements and they have internal dynamics. With regard to FSs, they usually contain saccades as gaze shifts. As seen in a study on the scene perception [19], the saccades are regarded as crucial features in eye movements.
tures in eye movements. We suppose that such saccades occur more actively when humans are in higher level of mental focus, and introduce a stroke length $e_{\text{fs}1}$ and a frequency $e_{\text{fs}2}$ of saccades as features of FSs. Let us use the notation $X^{(k)}$ for the velocity of an eye-motion pattern $X^{(k)}$, $||X^{(k)}||$ is thresholded at $N_{\text{c}}$, so that $N_{\text{c}}$ instances of partial temporal intervals $[O_{1}, \ldots, O_{N_{\text{c}}}]$ which contain saccades are detected. For each partial eye-motion pattern $X^{(k)} \oplus (x_{i} \mid t \in O_{i})$, we calculate the stroke length of saccades and then get the average value as $e_{\text{fs}1}$:

$$e_{\text{fs}1} = \frac{1}{N_{\text{fs}}} \sum_{i=1}^{N_{\text{fs}}} \frac{1}{\sqrt{\tau_{i}}} \left( \max_{(i,j) \in O_{i}} \left( ||X^{(i)} - X^{(j)}|| \right) \right).$$  \hfill (4)

where $a_{i}$ denotes the area size of a target flow at the time $O_{i}$ starts, $e_{\text{fs}1}$ is normalized by $\sqrt{\tau_{i}}$ because the length of saccades seems to depend on the target size, $e_{\text{fs}2}$ is defined as $e_{\text{fs}2} = N_{\text{c}} / \tau_{e}$, where $\tau_{e}$ denotes the duration of $X_{e}$.

Meanwhile for PSs, we consider the synchronization between eye movements and target flows. When humans track a moving object, they tend to synchronize the pursuit acceleration to expected changes of the target movement, and maintain the ve-

ture set for a saliency-dynamics pattern $p$, the elements of which denote features derived from eye movements observed in the pattern. For instance, if $p$ is MS, the observable eye movements are FS, NC, and XC (see Table 2). So $e_{p}$ can be represented as $e_{p} = [e_{\text{fs}1}, e_{\text{fs}2}, e_{\text{nc}}, e_{\text{xc}}]$. Each element of $e_{p}$ is here normalized into a range of $[0, 1]$. Notice that every type of eye movements can be observed more than once during a saliency-dynamics pattern. Therefore, we first calculate a feature from each eye movement, and then give the average value per each type of feature to the component of $e_{p}$.

Here we assume that the different levels of mental focus $R$ are described as $[R_{1}, \ldots, R_{N_{\text{R}}}]$. The estimation of mental focus is then formulated as a problem to estimate the state $\hat{R} \in [R_{1}, \ldots, R_{N_{\text{R}}}]$ which brings to a maximum a posterior probability from a new observation $e_{p}^{*}$, such as:

$$\hat{R} = \arg\max_{R} P(R|e_{p}^{*}) = \arg\max_{R} P(e_{p}^{*}|R)P(R).$$  \hfill (7)

Furthermore, in this paper we assume $P(R)$ as a constant, and transform the equation above into arg max $P(e_{p}^{*}|R)P(R)$. We build a discriminative model of mental focus levels from feature sets derived from training data, differently for saliency-dynamics patterns. And for the estimation, we switch the model according to the observed saliency-dynamics patterns.

5. Experiments

5.1 Experimental Setup

We conducted some experiments and estimated the level of mental focus. In these experiments, we aim to discriminate two levels of mental focus: high and low, as a relatively-simplified evaluation. 10 subjects took part in the experiments, and 12 TV commercial videos (15 sec) were employed. The commercial videos are originally designed to attract the attention, and therefore are expected to include some obvious saliency flows.

Environments and conditions

A subject sat in front of a screen\(^{12}\), and an eye tracker\(^{13}\) was installed below the screen. The eye-tracking accuracy was, on average, around 0.7°. The spatial distance between the subject and the screen was around 1000 mm, and in these settings eye movements could be observed during experiments.

Since the mental focus specifies an attentional state to video-viewing tasks, we adopt the following two conditions in order to control the level of the mental focus in the experiments:

Condition 1 (high level of mental focus) A subject watches a video and answers a simple interview after that.

Condition 2 (low level of mental focus) A subject watches a video, and besides he/she does a mental calculation while watching.

For each condition, subjects were asked to orient their gaze to a screen as far as possible. They carried out the tasks in the following sequence: video group A (six out of all the videos)—Condition 1, video group B (the other six videos)—Condition 2,

\(^{12}\) MITSUBISHI Diamondcrysta RDT262WH, 25.5 inch. W550 mm/ H544 mm.

\(^{13}\) Tobii X60 Eye Tracker. An approximate allowed range of head motion is $400 \times 220 \times 300$ mm.
video group B—Condition 1, and video group A—Condition 2.

Preprocessing and parameter setting
Eye-gaze data were acquired by the eye tracker at 30 Hz. As preprocessing, we applied a median filter with 0.5 sec window to the data in order to suppress spontaneous noises and to interpolate defects by eye blinks. The remaining defects of eye-gaze data caused by eyelid closures constituted 23.6% of the total sequences. For the saliency extraction, the parameter \( \pi \) in Section 2.1 was empirically defined as 0.1. Saliency areas then covered 31.5% regions of the total video frames, and the ratio of the state in which subjects looked at any saliency areas was 88.7%. For the saliency-dynamics analysis, the parameters \( \pi_c \), \( w_d \), \( w_s \), \( w_p \) (see Section 2.3) were defined as \( \pi_c = 2^\circ/s \), \( w_d = 2^\circ \) based on the size of the human central visual field, \( w_s = 0.1 \) sec and \( w_p = 0.5 \) sec to avoid creating short fragments of static flows and saliency-dynamics patterns. The reaction time of exogenous saccades \( \delta \) (see Section 3.3) was defined as 0.2 sec by following Ref. [18], and the threshold for saccade speed \( \pi_v \) (see Section 4.2) was defined as 8°/sec to avoid detecting fixations incorrectly.

5.2 Results and Discussions
Eye movement analysis
We aggregate feature sets for each saliency-dynamics pattern observed in the experiments. Since we used two conditions in the experiments to control the levels of the mental focus, the obtained data consists of two classes (high/low mental focus). Namely, the obtained feature sets constitute two conditional distributions, conditioned by the level of the mental focus. In order to verify the separability of these two classes in terms of linear discrimination, we first apply the linear discriminant analysis (LDA) to the obtained data set, and calculate partial F-Values to figure out which elements of the feature sets contribute.

Figures 6, 7, 8, 9 and 10 describe the relative frequency distributions of the data after LDA projection, in order to visualize the separability. Table 3 shows partial F-Values for each saliency-dynamics pattern. We can find that the importance of features varies according to the saliency-dynamics patterns, and these results also suggest the following aspects of gaze behaviors:

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*4 Since we employ sequences of eye-gaze points on a screen as eye movements, we do not regard the eye blinks especially in this paper, though some studies report on the effectiveness of eye blinks to estimate attention resource [21].
The level of mental focus mainly affects saccades which internally occur in FS/PS. We can find the above aspect from the partial F-Value of \( e_{s1} \), \( e_{s2} \) and \( e_{p2} \). Subjects seem to scan target flows actively rather than change them when they are in the high level of the mental focus, since all the NC/XC contributions are much smaller than the others.

Synchronization in the speed between eye movements and target flows is not affected much by the level of mental focus. That is, subjects basically tend to pursue dynamic saliency flows at any level of mental focus. That is because the partial F-Value of \( e_{p1} \) is relatively smaller than that of \( e_{s1} \) and \( e_{s2} \) in MSD, as well as that of \( e_{nc} \) and \( e_{xc} \) in MD.

We can find that the two relative frequency distributions are somewhat separated. Still, some of them are clearly impossible to separate linearly. Therefore, for the estimation, we employ the non-linear discrimination that directly estimates the conditional probability distributions.

### Mental focus estimation
Following Eq. (7), we estimate the level of mental focus. 24 data for each subject (totally 240 data), which consist of two levels of mental focus per each video, are obtained. We apply leave-one-out cross validation method to obtain the estimation accuracy for each saliency-dynamics pattern. Namely, we remove one of the 240 data to learn a conditional probability distribution using the rest of the data, and test the removed data to be classified correctly. To interpolate the obtained distributions, here we apply the additive smoothing with the empirically-defined smoothing parameter \( \alpha = 0.0001 \) to them. We iteratively change the feature set to remove so that we test all the data, and obtain the average accuracy per saliency-dynamics pattern.

Table 4 shows estimation accuracies. The accuracies are obtained for all the saliency-dynamics patterns and their average. Here we employ two estimation baselines. One utilizes gaze durations toward saliency areas as a feature of eye movements (see “Duration” in Table 4). We calculate temporal durations while subjects look at each saliency area, and get the average ratios between the durations and temporal intervals defined by saliency-dynamics patterns. From sequences of saliency-dynamics patterns, we obtain conditional probability distributions of the duration ratios for each level of mental focus, and utilize them for the estimation. The other utilizes PERCLOS [4] as a feature of eye movements (see “PERCLOS” in Table 4). In fact we simply calculate the average ratios between temporal intervals of eye-gaze data defects and those of saliency-dynamics patterns, instead of the duration ratios shown above.

We can confirm that estimations of all the patterns perform more accurately than the baselines. The proposed method switches different discriminative models for observed types of saliency-dynamics patterns. The results suggest that we can utilize better features in adapting to the changes of the saliency-dynamics patterns than uniform features employed in the baseline methods. Another difference of the proposed method from the baselines is that it focuses on the internal eye-movement dynamics in saliency areas. That is, the proposed method investigates not only “what subjects look at,” but also “how subjects look at,” and thus seems to enhance the accuracies.

From a viewpoint of improving the robustness of the method, one of the approaches is to vote estimation results within longer intervals. The estimation accuracy by integrating the results conducted in a single video interval (15 sec) is 93.3% on average. Besides, this paper conducts classification of two levels of mental focus as a relatively-simplified evaluation, but in principle, we can estimate multi-levels of the mental focus in the same fashion. Comparing the two baselines, PERCLOS employs gazes of both saliency and non-saliency areas whereas Duration employs those of only saliency areas. The difference in their accuracy suggests that gazes of the non-saliency areas also contribute the discrimination of the levels of mental focus. For the discrimination of saliency and non-saliency areas, we simply set a fixed threshold for all the saliency maps. Therefore, the saliency extraction employed here has a potential risk of regarding actual gaze targets as non-saliency areas. To overcome the problem, one possible way is to improve the thresholding method such as to select thresholds adaptively for each saliency map with consideration of its saliency-value histogram.

The videos we employed in the experiments contain some clear saliency areas, and therefore eye gaze seems to have a tendency to focus on those areas. However, to apply the proposed method to other kinds of videos, it is difficult to assume that clear saliency areas always exist. With regard to scenes with no saliencies such as plain natural scenery or scenes filled with saliencies such as crowds, the proposed method with a simple saliency extraction originally has a problem with the specification of objects to be looked at. For improvement of the saliency extraction, we can introduce some heuristics in conjunction with the saliency map; for instance, employing the saliency map with object detection such as face detection [22], [23] can enhance the saliencies of actual objects to be looked at, and therefore it can be helpful to specify them.

### 6. Conclusions
We proposed to analyze the spatio-temporal correlation of dynamics between the visual saliency and eye movements for mental-focus estimation. Experimental results reveal that this correlation can be a meaningful clue for the mental focus, and the
The proposed method performs accurately to discriminate two levels of them. This study introduces an analysis of eye-movement dynamics by categorizing them from the aspect of visual-saliency dynamics in view, in order to estimate the mental focus. On the other hand, we can also utilize this correlation in the form of the detailed analysis of the visual-saliency dynamics from the aspect of the eye-movement dynamics. That is, extraction and modeling of the visual-saliency dynamics allow taking actual eye movements and mental focus into account, as well as introducing heuristics shown in Section 5.2. Besides, we can confirm the effectiveness and the necessity of the proposed analysis, but its sufficiency has yet to be revealed. Future work will seek to generalize the analysis of the spatio-temporal correlation between visual saliency and eye movements, and to apply the proposed method to more general video-viewing scenes.

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Reference
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