Comparison between Touch Gesture and Pupil Reaction to Find Occurrences of Interested Item in Mobile Web Browsing

Shohe Ito[1], Yusuke Kajiwara[2], Fumiko Harada[3], Hiromitsu Shimakawa[4]

[1,2,4](Ritsumeikan University Graduate School of Information Science and Engineering, Japan)
[3](Connect Dot Ltd., Japan)

ABSTRACT : Web pages are full of interesting items people have never got familiar with. Mobile users often encounter new items interesting them, when they are Web browsing with their smartphones and tablet PCs. They usually find the new interesting items from pinpoint information such as one piece of phrase. To identify interests of web users, many existing methods utilize logs of Web pages the users visited. They cannot identify items the users get interested for the first time. This paper proposes two methods to estimate new pinpoint items interesting the users. One is the method with touch operations to estimate interested items. The other is the method with pupil reactions to estimate them. A part of a web page a user looks at is regarded as their interested items when touch operations or pupil reactions make a response relating on their interests. The methods can deal with users' interests, because touch operations and pupil reactions show their current interests. Users are able to enjoy the services provided according to their estimated pinpoint and current interests after the estimation of the interested items. When the proposed method with touch gestures estimates interested items, we calculated the precision, the recall and the F-measure for every subject. The mean of the precision, the recall and the F-measure are 0.691, 0.491, and 0.522, respectively. Similarly, when the proposed method with pupil reactions estimates interested items, we calculated the precision, the recall and the F-measure for every subject. The mean of the precision, the recall and the F-measure are 0.856, 0.426, and 0.483, respectively. Additionally, we focus on the evaluation results of each user. We discuss which methods should be used in each case.

KEYWORDS -Interest, Mobile Terminal, Pupil Movement, Recommendation, Touch Gesture.

I. INTRODUCTION

The population enjoying Web browsing with mobile terminals is rapidly increasing, as the mobile technologies get advanced. They encounter new interesting items when they browse. They are usually interested in not whole pages but pin point items such as specific phrases and images inside the pages. When they encounter the pinpoint interesting items which are unfamiliar to them, they really want information relevant to the items. Many methods are proposed to provide relevant information of items which interest users. However, all of the existing methods use the log of Web pages the users visited[1], [2], [3], which prevent the methods from identifying the new items in an on-line manner. This paper proposes two methods to estimate new pinpoint items users are interested. One is the method with touch operations. The other is the method with pupil reactions. When users encounter interested items during web browsing, they take specific touch operations, to watch the items carefully. On the other hand, pupils of human beings enlarge when they see interested objects. We identify either touch operations or pupil reactions correlated with users' interests. Identification of encounters of users with interested items allows us to estimate their pinpoint interests. Since touch operations and pupil reactions show their interests immediately, the method can deal with their new interests. Services such as recommendation of relevant information are provided based on the estimated pinpoint and current interests, after the estimation of these interested items. This paper shows estimations of the method with touch gestures and the method with pupil reactions based on data of users' web browsing.

II. INTEREST ESTIMATION DURING BROWSING WITH MOBILE TERMINALS
A. Web Browsing with Mobile Terminals

More and more people use mobile terminals such as smartphones, and tablets[4]. These users of mobile terminals usually browse web pages as well as enjoy calling and mailing[5]. On the other hand, many web pages are likely to have a lot of information[6]. Those web pages include e-commerce sites[7], news sites[8], restaurant guides[9], picture sharing sites[10] and so on. Mobile users often get to browse these big web pages.

When they browse the pages, they seldom browse the whole pages. When mobile users browse these big web pages, they usually read specific parts of these web pages because they have pinpoint interests in the parts. Mobile terminal can show limited parts of big Web pages. When users read big web pages, they cause the scope of mobile terminal screens to move.

Apart from this, mobile users usually browse web pages casually and briefly. For example, they browse web pages, to check news in trains, to look for restaurants in unfamiliar places, and to consult meanings of unknown words which appear on TV programs. In these cases, mobile users usually encounter new information, which brings new interests to the users.

A. Interest Estimation on Mobile Terminals

The paper aims to provide mobile users with services based on their interests when they browse big web pages. Suppose a mobile user browses the web pages about the London 2012 Olympics, "London 2012: Revisiting BBC Sport's most-viewed videos"[11]. This web page shows 50 impressive scenes of various kinds of sports on the 2012 Olympics. Such web pages have attractive items which interest many users. A specific user saw a title "The perils of courtside commentating" among various paragraphs of the web page, which brought a new interest to the user. This is the process that "The perils of courtside commentating" gets an interested item from an attractive item for the user. "The perils of courtside commentating" is an interested item for the user. He might want to get more information on the interested item expressed in the paragraph. If interested items are identified, we are able to provide users with services based on their interests, such as recommendations of other articles relating on the interested items.

Though there are many methods to estimate interests of users browsing web pages, the methods use records of web pages the users visit for the estimation. The methods estimating user interests cannot estimate interested items in web pages, in a pinpoint manner. The methods regard the whole web page as interested items of the users. In the methods, the user in the previous example is assumed to have interests in all of the 50 scenes. The paragraphs out of his interests prevent the estimation from identifying the user interest with high accuracy.

Furthermore, these existing methods cannot deal with new interests occurring suddenly, because they found on records of visited web pages. Suppose the user is apt to browse web pages about track and field events because he likes them. The methods based on the browsing logs estimate that he prefers track and field events from records of visited web pages. This paragraph tells a basketball game. It is difficult for the existing methods to recognize a new interest occurring suddenly for the paragraph about the basketball event.

III. INTERESTING ITEM ESTIMATION BASED ON PUPIL REACTION AND TOUCH GESTURE
B. Combination of Pupil reaction and Touch Gesture

We propose the two methods estimating interested items users encounter. One of these methods is based on touch gestures. The other is based on pupil reactions. When the method estimates estimating interested items, we consider not only the way to browse web pages on mobile terminals, but also processes users encounter interested items. Consequently, we selected touch gestures and pupil reactions as information correlated with users' interests in order to estimate users encounter interested items. In the future, the information can be acquired without loads on users when mobile users browse web pages. We refer to touch gestures as touch operations on a mobile terminal screen. On mobile terminals, users cause web pages to move so that parts they are interested in appear on the terminal screen. The web page is moved with touch gestures of users. Touch gestures are expected to estimate that users encounter interested items. Apart from this, human beings inherently open the pupils of their eyes when they encounter interested items. Measuring pupil reactioncontributes to identifying that users encounter interested items. Touch gestures and pupil reactions can detect the timing users encounter interested specific pinpoint items. Touch gestures and pupil reactions reflect current interests of users immediately. The proposed method identifies a part of a web page reflected on a screen of a mobile terminal when it estimates that users encounter interested items. We regard the part of the web page as an interested item. When the proposed method identifies an interested item, services are provided based on the interested item. Users can receive services relating on their pinpoint and current interests.
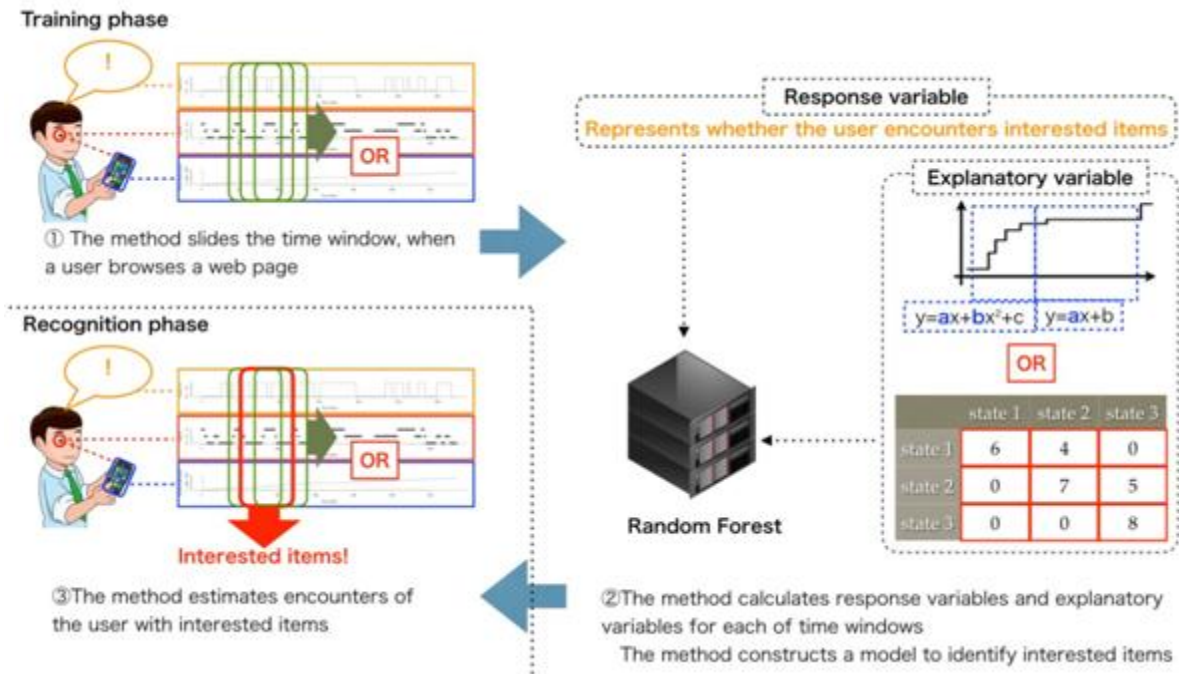
Figure 1: Outline of Proposed Method

Figure 1 shows the outline of the proposed method. Basically, the method with touch gestures and the method with pupil reactions take the same step. The proposed method divides into a phase learning models and a phase identifying interested items. First, these methods record encounters with interested items. At that time, if the method with touch gesture is used, touch gestures are recorded simultaneously. Similarly, if the method with touch gesture is used, pupil reactions are recorded. The analysis with the hidden Markov model divides pupil reactions into states. It enables pupil reactions to be expressed by state transitions of pupils. A time window slides on records the selected method needs. These records are acquired each of time windows. Second, response variables and explanatory variables are extracted from each of time windows. The method applies the random forest algorithm to data composed these variables to estimate interested items. Finally, a model constructed in the phase identifying interested items estimates interested items. Services based on interested items are provided after they are estimated. The services might include recommendations of web pages relating on the interested item, showing meanings of current topic words in the interested item, exhibiting advertisements based on them and so on.

A. Interested item Estimation by Touch Gestures

Ito and et.al have developed a method to estimate users' interest with touch gestures[18]. The paper [18] has shown that touch gestures with user-specific patterns appear when users encounter interested items during browsing a web page. The user changes the area of a web page displayed on a mobile terminal screen with touch gestures when he is browsing the web page. It means the history of touch gestures is expressed with a graph showing time-series of the displayed area. We refer to the graph as a gesture trail. Figure 2 shows a gesture trail. The horizontal axis of the graph shows the time. The vertical axis of the graph is the vertical position which the user is currently looking at in a web page. The vertical position is defined as the number of pixels from the beginning of the page to the top of the area displayed on the screen. Gesture trails such as Figure 2 show the history of touch gestures of swipe upward and downward to go on reading web pages. The position of the displayed area of a web page increases when a user goes on reading the web page downward. As a
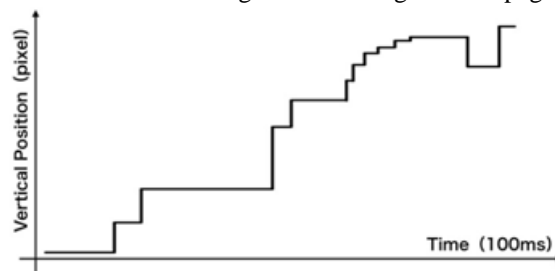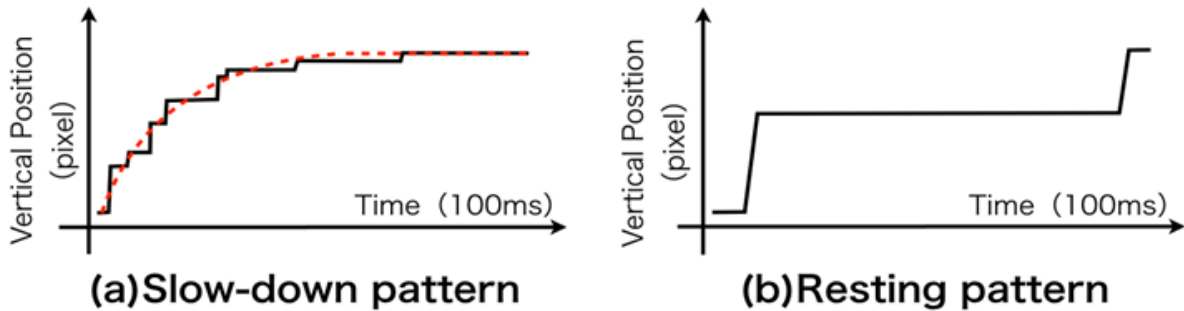

Figure 2: Gesture Trail

Figure 3: Gesture Patterns Proposed in [18]

consequence, the gesture trail is right-upward slope. On the other hand, the position of the displayed area decreases when a user goes back to a part of a web page which he looked at before. At that time, the gesture trail is right-downward slope.

The shape of a gesture trail reflects user's interest. The gesture trail of a specific shape appears when a user encounters an interested item. We have defined the gesture trail which appears at encounters of interested items as a gesture pattern in [18]. Two gesture patterns as shown in Figure 3 have been introduced in [18]: Slow-Down and Resting patterns.

- *Slow-Down pattern*···The degree of the slope in a gesture trail means the velocity to read a web page forward. The velocity and its acceleration are positive when a user goes on reading a web page. According to Figure 3 (a), the Slow-Down pattern is the gesture trail where the velocity is positive and the acceleration is negative. The Slow-Down pattern shows that a velocity in which a user read a web page is getting slow gradually. The decline of the velocity is caused by users' sudden encountering of interested items. The Slow-Down pattern shows interest occurring in a comparatively short time. When the Slow-Down pattern appears, it is considered that information unknown to the user incidentally induces a new interest in a web page.

- *Resting pattern*···According to Figure 3 (b), the "Resting pattern" shows that the vertical position of the displayed area stays at a same position for a period of time. When the vertical position stays at a same position, it is suggested that the user focuses on the displayed part of a web page corresponding to the position. Furthermore, it may be the situation that the user reads the part carefully and understands it deeply. There is a high possibility the user is interested in the web page article intentionally when the Resting pattern appears.

[18] proposed to observe gesture trail during browsing and detect the time zones where these gesture patterns appeared in order to estimate interested items. We estimate the part of the web page which a user browses on the identified time zone as an interested item. [18] assumed that durations of the Slow-Down pattern and the Resting pattern are same. In this research, we investigated the durations of the Slow-Down pattern and the Resting pattern. We found there is a difference between the durations of the two gesture patterns. Accordingly, we set the durations of the Slow-Down pattern and the Resting pattern separately in this research. The Slow-Down pattern usually takes around 1500 ms, while the Resting pattern around 3500ms
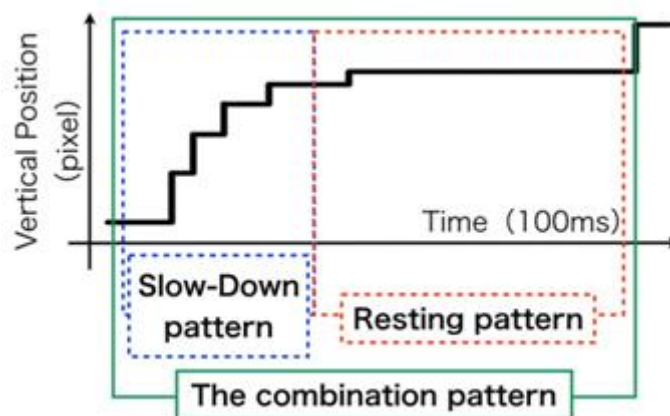

Figure 4: Slow-Down-to-RestingPattern Serie

E. Noise Reduction

The interested item estimation method of [18] does not address a gesture trail which resembles the gesture patterns of users reading out of an interested part. Such gesture trails degrade the precision in the interested item estimation. Such gesture trails appear when users look away during browsing a web page. Personal habits and operation errors of mobiles may also cause them. This research introduces a combined gesture pattern which is the sequence of Slow-Down and Resting patterns to detect encounters of users with interested items. The Slow-Down pattern followed by the Resting pattern is defined as the combined gesture pattern in this research. We call the combined gesture pattern as the Slow-Down-to-Resting pattern. Figure 4 shows the Slow-Down-to-Resting pattern. We regard that a user encountered an interested item in a time duration if the Slow-Down-to-Resting pattern detected in the gesture trail during the time duration. The Slow-Down-to-Resting pattern shows the series of the following behaviors. First, a user reduces the velocity because he goes on reading a web page when he encounters an interested item. Second, the user reads the interested item carefully. There is the high possibility that the areas users encountered are interested items when such series occur. We are able to identify interested items more accurately using Slow-Down-to-Resting pattern. Slow-Down patterns and Resting patterns are approximated with the following functions.

$$y = ax^2 + bx + c \qquad (1)$$
$$y = ax + b \qquad (2)$$

The Slow-Down pattern is approximated by the quadratic function of Equation (1). Similarly, the Slow-Down pattern is approximated by the linear function of Equation (2). The proposed method uses coefficients of these functions as explanatory variables. Coefficients affecting shapes of two gesture patterns are regarded as explanatory variables. Explanatory variables of Slow-down patterns are "*a*" and "*b*" of Equation (1). Coefficient *a* shows how moderate Slow-Down pattern curve. Coefficient *b* decides positions of Slow-Down patterns on a horizontal axis. The explanatory variable of Resting patterns are "*a*" of Equation (2). Gesture trails approximated by Equation (2) are regarded as Resting patterns when *a* is close to zero.

A. Pupil Reaction in Reading Interested Item

The Human beings inherently open the pupils of their eyes when they encounter interested objects. Identification of pupil reactions relating on users' interests leads to the estimation of interested items in web pages. An in-camera is attached on a mobile terminal screen. The cameras are able to take pupil reactions without loads for users. However, the current camera does not have enough performance to take pupil reactions. There are several approaches to take pupil reactions[20]. Improvement of in-cameras is expected so as to develop the proposed method with in-cameras.

Figure 5 (a) depicts the graph showing time zones a user encounters interested items. These horizontal axes of this graph represent the time divided by every 100 ms. The vertical axis of this graph shows whether a subject encountered an interested item or not. This graph is generated by the actual data through an experiment
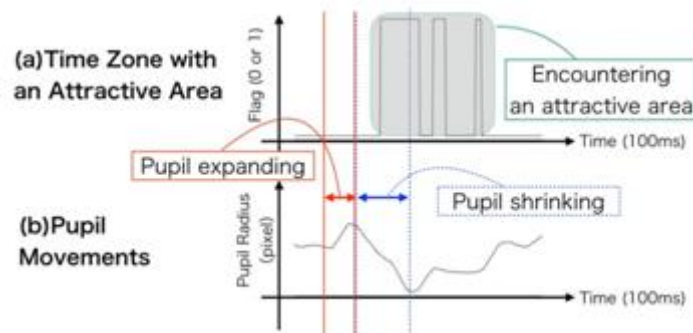

Figure 5: Graphs of Encounter with Interested Items and Pupil Reactions

explained in the following section. In the experiment, a user presses a foot pedal when he encounters interested items during browsing a web page. A user shows an encounter to an interested item by pressing on a foot pedal when the vertical axis of the graph is one. Figure 5 (b) is the graph showing pupil reactions. The vertical axis of this graph is the pupil radius by pixel. These two graphs show that the user's pupil expands before he encounters an attract area. After the user's pupil expands, the pupil shrinks in a little time. The pupil seems to return to the former stable condition.

Using Figure 5, we discuss detection of the pupil reactions on encountering interested items. The analysis with the hidden Markov model divides pupil reactions into three states. In this research, we assume that the pupil reactions expressed by the graph (b) follow the hidden Markov model which presents the pupil radius using

three hidden states. Based on the model, we identify the history of hidden state transition corresponding to the time series of pupil radius as Figure 5(b). We suppose that pupil reactions are divided into three states as follows.

- State 1 … The state where the pupil finishes expanding and starts shrinking
- State 2 … The state of the interval between expanding and shrinking
- State 3 … The state where the pupil finishes shrinking and starts expanding.

We focus on transitions of these states to identify pupil reactions when users encounter interested items. For example, the user of Figure 5 encounters an interested item. At that time, first, his pupil expands. Next, it shrinks. The transitions of the pupil states are State1, State2, and State3, in order. The identification of the series of these states enables us to estimate encounters with interested items. The proposed method uses the transition of pupil states as explanatory variables. We address the transition from 3 states to themselves. It takes 3^2, that is, 9 explanatory variables. The method with pupil reactions identifies users' encountering interested items with these nine explanatory variables.

IV. EXPERIMENT TO EVALUATE THE PROPOSED METHOD

B. Outline of Experiment and Evaluation

When subjects browse web pages, we experimented to record touch gestures, videos of pupils and their encounters with interested items. We evaluate the method with touch gestures and the method with pupil reactions based on these records. Four subjects conducted an experiment as follows.

1. We explain the outline of the experiment to give a task to each of the subjects. The task is to summarize how to grow certain farm products on a document.
2. The subject browses the selected web page whose content includes how to grow the farm products. When the subject browses the selected web page, we recorded touch gestures and a video of his pupil.

The subject showed time zones when he encountered interested items by stepping on a foot pedal. The subject stepped on the pedal at the moment when he encounters interested items. The subject kept stepping on the pedal during reading these interested items. The time of the subject stepping on the pedal was recorded automatically. We measure the time-series of radiuses of the subject pupils from videos after the experiment. We use leave-one-out cross-validation to evaluate the proposed method. Figure 6 shows how to divide subject's records

Figure 6: Division into Test Data and Training Data

into test data and training data. A time window slides records acquire when a subject browses a web page. One of the records of every time widow is regarded as a test data. Similarly, the time window also slides records out of test data. All of the records are training data. The proposed method distinguishes test data showing that users encounter interested items from others. At that time, we calculate the precision, the recall and the F-measure.

A. Recording Touch Gesture

We used the tablet terminal "ASUS MeMO Pad 8 ME581C" in the experiment. The tablet terminal works on android 4.4.2. The screen size is eight inches. We put an anti-glare film on the tablet terminal screen to reduce the brightness of the screen. It prevents the brightness of the screen from affecting pupil reactions. We implemented a web browser application to record touch gestures. The application shows the web page we selected when a subject activates it. Every 100 ms, the application records positions which the subject watches in a web page, while the subject browses the web page.

B. Recording Video of Pupil

The facility recording videos of pupils is like Figure 7. A subject puts his chin on the chin-support when he browses a web page. The chin-support prevents the vibration of subject face, stabilizing the video of the pupil. In addition, when they use mobile terminals, they usually take slouching position because of the influences of light or their eyesight. The chin-support enables the subject to reproduce the position that he takes during he is browsing web pages. It also fixes his face, because of the weight of his head. It is difficult to film pupils using in-cameras of current mobile terminals. We filmed pupils with infrared ray in order to make it easy to identify the pupils[21], [22], using the camera, Canon ivis FS10. The infrared film on the camera cuts off visible light. The infrared film we used is "FUJIFILM IR-76 7.5x7.5". We irradiated the infrared ray surrounding subject eyes when we use the camera with the infrared film. We used 56 infrared LEDs to irradiate infrared ray.

C. Recording When Subjects Encountered Interested items

Subjects use a foot pedal to suggest the time zones where they encounter interested items in the experiment. These subjects are able to indicate their time zones without preventing their touch gestures because they use a foot pedal to suggest that they encounter interested items. These subjects are stamping the pedal in the time duration where their interested items appear. They keep stamping the pedal while he browses these interested items. The time zones that they stepped on the foot pedal are recorded automatically. The proposed method gets records of the pedal in every time window. The response variable in the method is whether records of time windows show these subjects encounter interested items or not. The proposed method identifies the maximum number of times they stamp the pedal in a time window. If the number of times these subjects stamps the pedal is larger than the half of their maximum number, we regard the time windows as ones showing they encounter interested items.
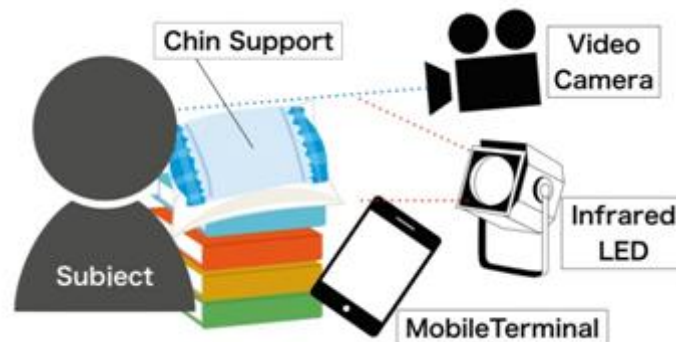

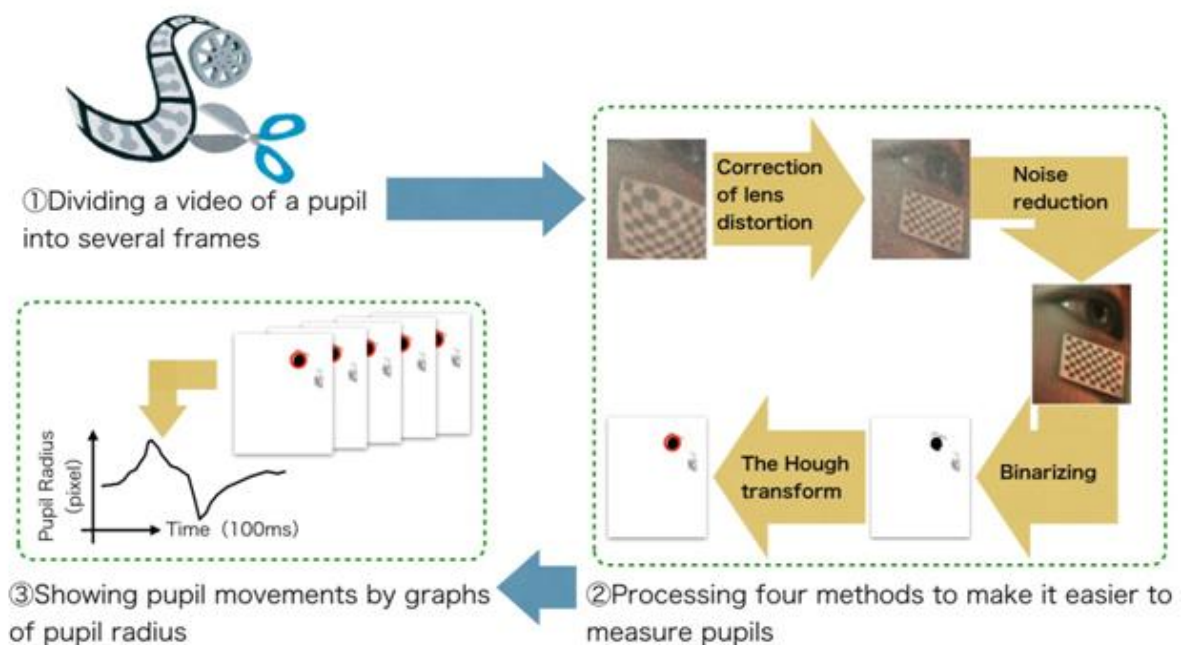Figure 7: Facility to Record Pupil Videos

Figure 8: How to Measure the Time-Series of Pupil Radius

K. Measurement of Pupil Radius

We generated the time series of pupil radiuses from the videos of pupils after the experiment. Figure 8 shows how to measure of the time-series of pupil radiuses from a video of a pupil. First, the video of a pupil is divided into each frame. Second, the picture of each frame is processed in order to make it easy to measure pupil radiuses in the picture of the frame. A lens distortion of the camera is reflected on the picture in each frame. We revise the lens distortion by the Zhang's method[23]. These frames have noises due to the infrared ray. We apply the bilateral filter to the frame to remove the noise. After that, we binaries the frame and extract the part of the pupil. The Hough transformation is applied to the frame. The transformed picture shows the edge of the pupil. Finally, we extract a circle in the frame picture by the Hough transformation as the pupil's radius. The Graph of pupil radiuses along the time series shows pupil reactions. We use the graph to analyze pupil reactions. In addition, we calculated relative errors between theoretical values and measured values to examine the performance of the pupil measurement method. We selected 50 frames of the picture of the pupil randomly from all frames of the video of a subject. The values of the pupil radius which we measured manually are theoretical values. The values measured by the pupil measurement method are measured values. Every mean of relative errors between theoretical values and measured values is 0.0668.

L. RESULT OF EVALUATION

We calculated the precision, the recall and the F-measure at the time when the two proposed methods estimate encounters with interested items. Table 1 shows these values we calculated.

Table 1 : Evaluation of Proposed Methods

Subject	Method	precision	recall	F-measure
1	Gesture	0.829	0.871	0.849
	Pupil	0.717	0.806	0.757
2	Gesture	0.688	0.074	0.134
	Pupil	1.000	0.128	0.228
3	Gesture	0.636	0.394	0.487
	Pupil	0.909	0.141	0.244
4	Gesture	0.611	0.625	0.618
	Pupil	0.802	0.628	0.705
mean of all subjects	Gesture	0.691	0.491	0.522
	pupil	0.856	0.426	0.483

V.   DISCUSSION ON APPLICATION OF PROPOSED METHODS

According to Table 1, we discuss cases applying the method with touch gestures and the method with pupil reactions. This discussion is based on two aspects. One is how well the constructed models estimate interested items. The other is the aspect of features of users' physical and their web browsing.

M. How Well Model Identifies Interested Items

According to evaluate results of every subject, the precision of the method with pupil reactions is higher than the one of the method with touch gestures. However, the numbers of subjects whose recall and F-measure are high are same in both of the method with touch gestures and the method with pupil reactions. We need to select one of these two methods so as to be appropriate to each subject from when we focus on the stability of estimating interested items. In the learning phase, we construct two models by touch gestures and pupil reactions. At that time, the consideration of identification rates of these models enables us to apply appropriate methods to each user.

N. Characteristics of Users

Some characteristics of users prevent either of the methods with either touch gestures or pupil reactions from estimating their interested items. We need to select either touch gestures or pupil reactions to estimate interested items. This selection discusses users' characteristics.

In this experiment, we were able to observe changes of subjects' pupils. However, we are not able to observe some shapes of users' eyes. We are not able to estimate their interested items by their pupil reactions. We need to use touch gestures for these users.

In addition, some users are difficult to get Slow-Down-to-Resting patterns correlated with their interests. We are not able to estimate their interested items by touch gestures. At that time, we need to use pupil reactions to estimate their interested items.

VI. CONCLUSION

This paper proposed a method to estimate user's interested items in a web page with touch gestures and pupil reactions during user views the page on mobile terminals. When the user gets attracted by a specific part of the page, the proposed method instantaneously finds which area currently interests him in detail. Such estimation can activate services based on the found detailed and temporal interested items.

This paper showed our evaluation of the proposed methods. When the method with touch gestures estimates users encounter interested items, the mean of the precision, the recall, and the F-measure are 0.691, 0.491, and 0.522, respectively. Similarly, when the method with pupil reactions estimates users encounter interested items, the mean of the precision, the recall, and the F-measure are 0.856, 0.426, and 0.483. Furthermore, we discussed cases using these two methods based on two aspects. One is how well the models estimate interested items. The other is users' characteristics.

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