Analysis of Trends in the Occurrence of Eyeblinks for an Eyeblink Input Interface

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***Abstract*—This paper presents the results of the analysis of trends in the occurrence of eyeblinks for devising new input channels in handheld and wearable information devices. However, engineering a system that can distinguish between voluntary and spontaneous blinks is difficult. The study analyzes trends in the occurrence of eyeblinks of 50 subjects to classify blink types via experiments. However, noticeable differences between voluntary and spontaneous blinks exist for each subject. Three types of trends based on shape feature parameters (duration and amplitude) of eyeblinks were discovered. This study determines that the system can automatically and effectively classify voluntary and spontaneous eyeblinks.**

***Index Terms*—eye blink input, input interface, voluntary blink, automatic classification, wearable computing.**

I. Introduction

Research into new communication channels between humans and computers has examined the interfaces of controlled devices such as smartphones or smart glasses for their potential to detect eye movements and other facial actions. Eyeblinks have been studied as possible sources of input for control interfaces. Thus far, blink input systems have been developed with the aim of helping severely physically handicapped people, such as ALS patients, communicate in their daily life [1–2]. In addition, the emergence of advanced technologies such as wearable devices has increased expectations for interfaces enabled for blink input [3–4]. If implemented, such devices should have an input interface that can be manipulated easily by users whose hands might be occupied already.

Eyeblinks can generally be classified into three types: voluntary, reflex, and spontaneous [5]. Voluntary blinks are those that are consciously produced, or as in this study, performed at the behest of the researcher. Reflex blinks occur because of external stimulation, such as photic or auditory stimuli. Last, spontaneous blinks are those that occur unconsciously. An effective eyeblink input system must employ a timing mechanism that interprets user intentions and his or her blinks. This means that the device must only read and interpret voluntary blinks and not reflex or spontaneous eyeblinks that are not meant for input. To this end, the system must be able to distinguish and correctly classify different types of blinks. However, automatic classification of eyeblink types is difficult because an eyeblink is a quick operation and individuals produce a wide variety of them.

This study aims to develop an eyeblink input system that can be installed on common information devices, such as smartphones or smart glasses. By using image analysis [6–7], the researchers in this study obtained and examined shape feature parameters in an eyeblink waveform (i.e., the waveform that measures the time evolution of the eyeblink process) and observed differences between voluntary and spontaneous blinks among subjects [8].

However, the hypothesis in paper [8] is not verified statistically. In contrast, our paper presents trends in the difference of shape feature parameters between voluntary and spontaneous eyeblinks. As a result, our paper investigates parameter distribution and statistically verifies the trend of the three groups shown as a hypothesis by measuring the data of many subjects. In addition, our paper investigates whether the burden of performing input operations using eyeblinks can be reduced; such investigation is performed by comparing the proposed method with a conventional method, based on user subjective evaluation after the experiment.

II. Related Works

Conventional eyeblink input systems are classified into two basic types. The first type uses input based on pre-established time values (for example, when a user closes the eyes for more than 200 ms) [3, 9–10]. In this case, a dynamic threshold value is used for each type of eyeblink because eyeblinks show wide individual differences. False input might arise if the threshold is fixed because the input time is dependent on each user; a user might unconsciously produce considerably short or long eye movements. The second type examines special eye movements, such as double eyeblinks or winks [2, 11–12]. However, these systems require the user to perform conscious and occasionally complex actions, and therefore, users need to learn to use these systems. In addition, these unusual eyeblinks can cause user stress, especially when the systems are used over a long period [1,5].

To solve these problems, eyeblink input interfaces have been studied to incorporate more natural eyeblinks. However, a user who does not display a noticeable difference in shape feature parameters between voluntary and spontaneous eyeblinks must be conditioned and encouraged by the system for it to accurately measure voluntary eyeblinks [1–6]. Therefore, the system designed in this study uses a messaging system—for example, it announces to a user, "you blinked correctly at the perceived signal"—to decrease user stress and to amplify the difference of shape feature parameters. This system most closely approximates an actual eyeblink interface because it is expected that the user is conscious of input when blinking, even if no user training has been conducted.

III. Measurements of an Eyeblink Waveform

If the time evolution of the eyeblink process can be accurately measured, it is possible to express an eyeblink as a waveform. Individual eyeblinks must be measured and then analyzed for automatic classification of eyeblink types. The typical techniques for sampling eyeblink waveforms are Electrooculugram (EOG) and image analysis. The EOG method involves placing an electrode on the skin near the eyeball. Eyeblink waveforms are then collected by recording changes in the cornea-retina potential. Until recently, this technique was proposed for automatic detection of voluntary eyeblinks [13]. However, the EOG method requires a unique apparatus to process ocular potential, and the user must have an electrode attached to the skin. Therefore, the EOG method is unsuitable for a simple interface. Moreover, extraneous noise from a living body can cause interference. By contrast, the method of image analysis examines pictures of eyeblinks captured by a video recorder. It has become popular because it requires no bodily contact and is manageable and adaptable. However, eye movements are difficult to capture with a video camera that has a standard aspect ratio (NTSC) because an eyeblink is a high-speed operation. Therefore, this study incorporates an algorithm used in previous research [6] that detects changes in eye aperture. It samples at 1/60 s using interlaced NTSC video images further divided into field images. Figure 1 shows a processing flow for detecting changes in the eye aperture area.

When image analysis is used, the first step is to analyze video images of the area that surrounds the eye in order to assess changes in eye aperture using binarization based on flesh color. Figure 2 shows an example of changes that occur in the eye-aperture area. Change data shown in Fig. 2 include changes in the eyeblink waveform. The next step applies smoothing differentiation between the split field area and the next split field. Coordinates that reveal the maximum area difference value and the minimum area difference value are determined using a second differentiation.

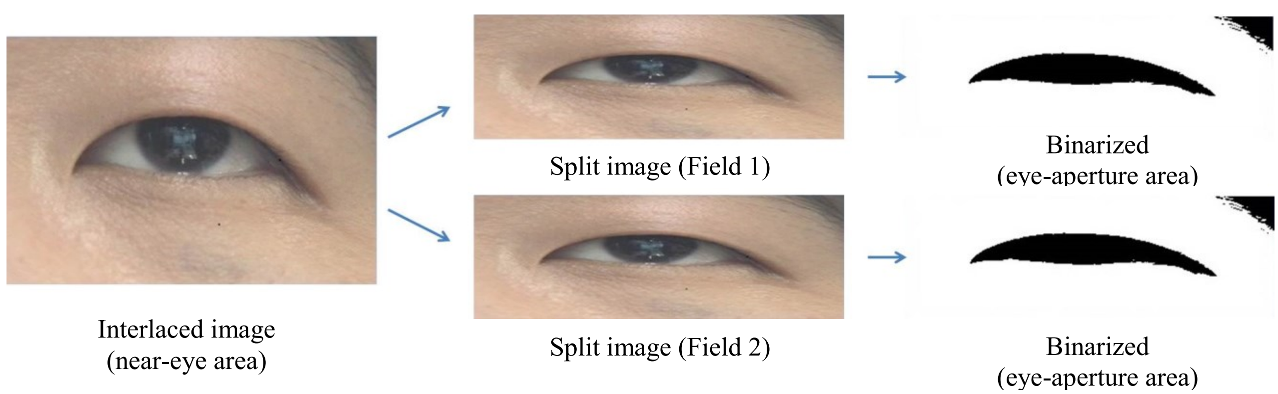

Fig. 1. Overview of frame splitting method and binarization.

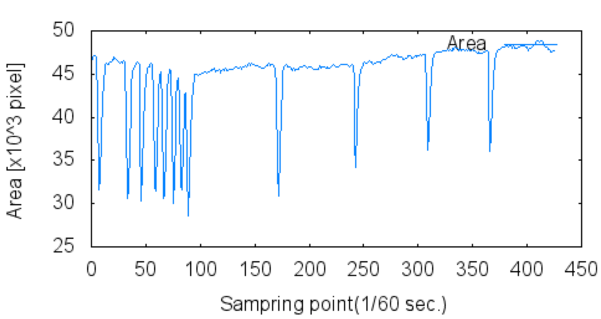

Fig. 2. Changes in eye-opening area.

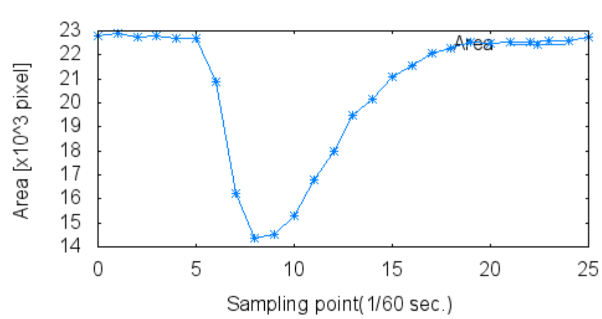

Fig. 3. Example of eyeblink waveform.

However, this step in the analysis involves excessive noise. This noise means small movement in the vicinity of the eye, such as from an eyelid. Therefore, researchers remove three coordinate classes of extreme value (maximum, minimum, and few-moving) using the *k*-means method. The study determines the start and end of an eyeblink waveform using the maximum and minimum values of the eyeblink waveform because one eyeblink waveform contains one maximum and one minimum value. Minimum values exist in the opening phase and maximum values exist in the closing phase. The study obtains data from one eyeblink waveform according to these factors. If the obtained maximum and minimum values are observed in succession as two points, the study uses the point closer to the field of temporal axes. An eyeblink start field is calculated by differentiating between field areas in the direction opposite to that of the temporal axes from the maximum value's field. In this field, the threshold Th_1 becomes positive for the first time. By contrast, the eyeblink end field is calculated by the difference between the field areas in the forward direction of temporal axes from the minimum value's field. In this field, the threshold Th_1 becomes negative for the first time. The threshold Th_1 is then determined by the following equation.

$$Th_1 = f(n) - f(n+1), \tag{1}$$

where n is the attention field and $f(n)$ is the eye-opening area in the n field. Figure 3 shows an example of the detected eyeblink waveform.

IV. Shape Feature Parameters of Eyeblinks

Eyeblinks vary widely by individual, but in most cases and during a voluntary eyeblink, the eyelids close completely. In addition, variation is relatively small in an individual, according to the eyeblink waveform. Therefore, this study focuses on the following parameters: closing-phase amplitude, opening-phase amplitude, and eyeblink duration as referred to in a previous study [1]. Figure 4 shows a model of an eyeblink waveform in which the closing-phase amplitude *Acl* is defined as the height of the closing-phase starting point *Ps* to the most minimum point *Pmin. Pmin* is defined as the point where an eye-opening area is smallest; that is, from the closing-phase end point *Psb* to the opening-phase starting point *Peb*. Similarly, the opening-phase amplitude *Aop* is defined as the height of the minimum point *Pmin* to the opening-phase end point *Pe*. Finally, the eyeblink duration *Dur* is defined as the field count from *Ps* to *Pe*.

The eyeblink waveform that is measured by means of either the EOG technique or image analysis can be applied to a model of Fig. 3. The eyeblink duration is represented as field numbers from the eyeblink starting point to the eyeblink end point. The eyeblink amplitude is represented as changes in the eye-aperture area. The point *Pmin,* at which an area is minimized, is determined based on the model (Fig. 4) in theory. However, it might not be determined by an actual measurement (Fig. 5). Therefore, *Pmin* is defined as the average of the eye-aperture field areas that are less than the threshold Th_2 in one eyeblink waveform. The threshold Th_2 is determined by the following equation.

$$Th_2 = \frac{Amax - Amin}{10} + Amin, \tag{2}$$

where *Amax* and *Amin* are the maximum and minimum, respectively, of the eye-opening area of the eyeblink waveform. In addition, the closing-phase amplitude is calculated based on the difference between the area of the eyeblink starting field and the point *Pmin*. Similarly, the opening-phase amplitude is calculated based on the difference between the area of the eyeblink end field and the point *Pmin*.

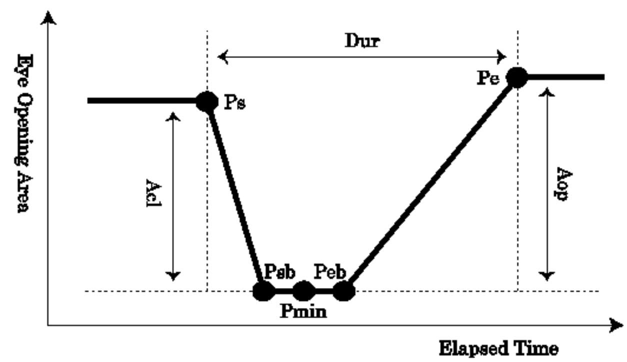

Fig. 4. Model of eyeblink waveform.

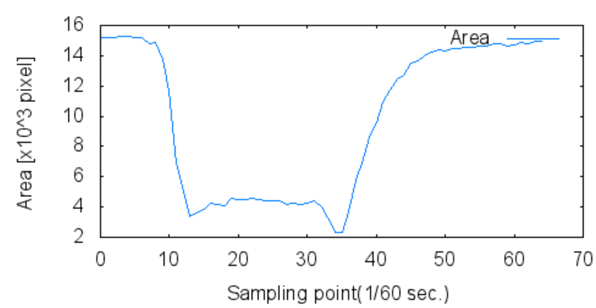

Fig. 5. Example of difficult-to-decide minimum point.

V. Measurement Experiments

This study employs the eyeblink waveform measurement algorithm discussed previously and measures the eyeblink waveform of 50 subjects (37 men and 11 women ranging in age from 20 to 29, and two women raging in age from 30 to 39, none with disabilities) to analyze the periodicity of shape feature parameters of eyeblinks.

The subjects were selected based on the age of individuals more likely to use smart devices predominantly.

A. System Outline

The hardware for the study's experimental system includes a Sony HDR-HC9 digital camcorder that is used to obtain eye images, and a personal computer used for image and eyeblink waveform analysis. Although the camera can capture high-definition (HD) pictures, standard-definition (SD) pictures are used in the experiments. The system is intended to be mounted on wearable and smart devices. Furthermore, the experimental system was developed to be a prototype.

Ordinary indoor lighting (incandescent lighting) was used when capturing moving images. A pair of light-emitting diodes (LED) was then placed symmetrically on both sides of the camera and at a distance of approximately 60 cm directly in front of the face of a subject. The back of the subject's head was lightly supported with a stabilizing device to prevent the head from shaking. The video camera was placed in front of and below the subject's head at a distance of approximately 20 cm. The camera then magnified and obtained pictures of the area surrounding the subject's left eye. Because the image format was set for SD video, the resolution was 720 × 480 pixels with a 16:9 aspect ratio and refresh rate of 30 fps (NTSC). These experiments were performed on the naked eye, and therefore, eyeglasses were not allowed during filming.

B. The Method of Experiment

The subjects were given the following instructions during filming:

1) *"Pay attention to the silver dot mark located on the upper part of the camcorder." (The mark was placed at this location by the researchers.)*

2) *"Do not resist the unconscious urge to blink."*

3) *"If you hear a signal, you must blink well always."*

The "blink well" instruction is meant to increase the difference of the shape feature parameters between voluntary and spontaneous eyeblinks. In other words, the signal is a means of encouraging subjects to be strongly conscious of their voluntary blinks. The signal was sounded randomly at intervals of 4 s to 10 s using a digital timer. Images were captured for approximately 90 s during the course of the experiment.

At the conclusion of the experiment, the subjects were asked to write questions and/or comments about their experiences during the experiment. The items in question were age, gender, sleep time during the previous night, health condition (five level: one means bad and five means good), task difficulty (five level: one means easy and five means difficult), confidence of achieving task (five level: one means low and five means high), and personal interpretation of "blink well."

C. Results

Table I provides data for subjects that show a significant difference in measurements between voluntary and spontaneous blinks. Table I displays the representative results of the experiment in relation to measured voluntary and spontaneous blinks. The table shows the average values of the durations of blinks, the closing-phase amplitude, and the opening-phase amplitude. Figure 6 shows a histogram that summarizes the distribution of the average value of eyeblink duration of the 50 subjects by eyeblink type. Figure 7 shows a histogram that summarizes the distribution of the average value of eyeblink amplitudes of the 50 subjects by eyeblink type.

The study administered a t-test to the subjects using a 1% standard deviation between voluntary and spontaneous parameters. Table II shows the tendency of significant difference of all parameters from the t-test results of the subjects. Use of the amplitude ratio of the closing phase to the opening phase for parameters is complicated because the ratio of the closing-phase to the opening-phase amplitude is, in all cases, found to contain a minimum of one large parameter. Therefore, the study redefined the average value of two amplitudes as the eyeblink amplitude.

TABLE I. RESULTS FROM EXTRACT PARAMETERS EXPERIMENT (TEN OUT OF 50 SUBJECTS, AND AVERAGE)

Subject	**Voluntary**				**Spontaneous**			
	Counts	***Dura [ms]***	***Acl [pixels]***	***Aop [pixels]***	***Counts***	***Dur [ms]***	***Acl [pixels]***	***Aop [pixels]***
A	14	421 *	8399 *	8454 *	19	297	5594	6742
B	15	480 *	6684 *	6681	55	352	4986	6152
C	15	674 *	12 285	12 810	21	498	11 073	12 338
D	14	382	21 273	24 206 *	7	464	18 673	19 635
E	12	461	18 908 *	20 666 *	18	353	13 311	15 120
F	15	475 *	8703 *	9231 *	20	360	6995	7911
G	14	423	12 093	13 504	5	366	12 135	13 697
H	15	560 *	11 312 *	11 665	16	351	8019	10 335
I	15	567 *	8253	10 448 *	5	270	7194	8875
J	13	898 *	13 064 *	12 657	17	380 *	9970	12 373
Average (50 subjects)		573.24	10 619.92	11 334.68		390.9	8398.28	9702.54

*<0.01 Significance difference

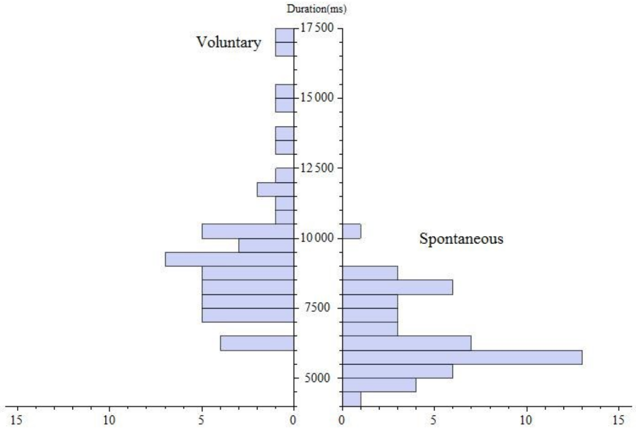

Fig. 6. Duration difference in every group.

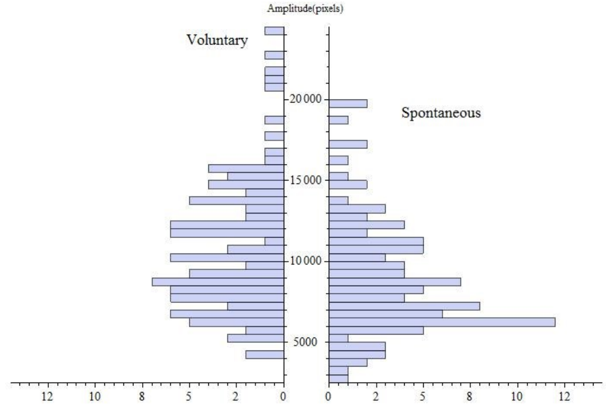

Fig. 7. Amplitude difference in every group.

TABLE II. Tendency Toward Significant Difference

Parameter	Amplitude significance	Amplitude no significance
Duration significance	46.0% (23 subjects)	24.0% (12 subjects)
Duration no significance	22.0% (11 subjects)	8.0% (four subjects)

In Table II, the tendency for variation in individual differences between voluntary and spontaneous eyeblinks is as follows. A significant difference in eyeblink duration is found to be 24% (12 subjects). For eyeblink amplitude, the difference is 22% (11 subjects). For both parameters, the significant difference is 46% (23 subjects). Finally, no significant difference is found in 8% of the subjects (four). In other words, a significant difference in shape feature parameters between voluntary and spontaneous eyeblinks is seen in a minimum of 92% of the subjects. Moreover, after individual parameters are examined, the following is clear. The total percentage of subjects who show a significant difference in eyeblink duration is 70%. The total percentage of subjects who display significant difference in eyeblink amplitude is 68%. Finally, the total percentage of subjects who show significant difference in both parameters is 46%.

D. Discussion

This study analyzes subjects who either do not show significant difference or show only some difference in shape feature parameters. The number of spontaneous eyeblinks is found to be limited. Two reasons explain this. The first is the fact that few blinks actually occurred, which might be because subjects were under stress during the experiment. The second is that eyeblinks register in movements that are too small to detect accurately. Therefore, this study might promote future research in eyeblink detection accuracy. However, a meaningful tendency is seen in approximately four subjects who also showed no significant difference.

Following the experiments, the researchers conducted interviews with the subjects. Some subjects did not perform eyeblinks consciously when signals were given because their spontaneous eyeblinks occurred at the same rate. Based on these interviews, the study will revise future instructions for clarity. In addition, the classification of eyeblink types can be improved based on those subjects who did not show significant difference.

The study defines Group A as the subjects who showed significant difference in eyeblink duration only (12 subjects). Group B consists of subjects who demonstrated significant difference in eyeblink amplitude only (11 subjects). Group C is comprised of subjects who showed significant difference in both parameters (23 subjects). Finally, Group D consists of subjects who did not show significant difference in any of the shape feature parameters (four subjects). The study uses a Mann–Whitney U test with a 1% standard deviation between the average of all subjects and that of each group for each parameter. Figure 8 shows the duration results. Figure 9 shows the amplitude results.

Figure 8 displays significant differences in the average duration values between voluntary eyeblinks and spontaneous eyeblinks as seen in Groups A and C. Figure 9 reveals significant differences in the average amplitude values between voluntary and spontaneous eyeblinks as seen in Groups B and C. These results show that an algorithm can classify eyeblink types automatically using one threshold for every group; thus, the algorithm can classify subjects into groups based on the shape feature parameters obtained. In other words, a conventional problem can be solved by classifying subjects based on the trend of parameters that appear in the voluntary eyeblinks of subjects. Thus, because eyeblinks vary dramatically among individuals, the problem of automatic classification can be solved using a single threshold.

The tendency of occurrence of shape feature parameters in a voluntary eyeblink are classified into three main groups based on eyeblink duration, amplitude, and both parameters combined. This means that, when conventional classification methods are employed that use eyeblink duration as the classification threshold, approximately 30% of the time a subject can be difficult to classify based on eyeblink type. In addition, a subject who does not show a significant difference in eyeblink duration, but shows a significant difference in eyeblink amplitude, occurs at a rate of 22%. Overall, it is determined that a shape feature parameter suitable for each subject must be selected to ensure proper classification of eyeblink types.

Among the items in question, we confirmed that the health condition of a subject and the sleeping duration the previous night do not affect the results in particular. In addition, the total result of the interpretation of "blink well" is confirmed by the number of 50 subjects: "make a long eyeblink" was indicated by 32 subjects, "make a strong eyeblink" by 16 subjects, and "quick eyeblink" by 2 subjects. These results are approximately the same as the numbers shown in Table II. Furthermore, the results of the subjective five-level evaluation for system usability (task difficulty, confidence of achieving task) are an average of 2.6 and 3.8, respectively, for the 50 subjects. These results show that the burden of input is not greater than the methods in other studies. In this regard, UI experiments are necessary for the objective assessment of usability and operability. In addition to the aforementioned method, and in order to compare our proposed method with the method of paper [2] and the method of paper [3] using the same user interface (UI), We conducted experiments on smart devices to determine the ease of input of each scheme. One example of such experiments is returning a signal to the subjects when they successfully provide an eyeblink input.

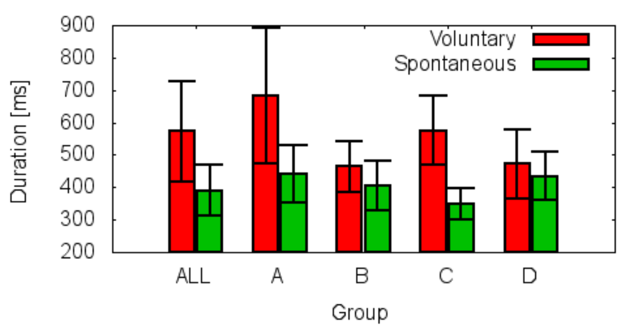

Fig. 8. Duration difference in every group.

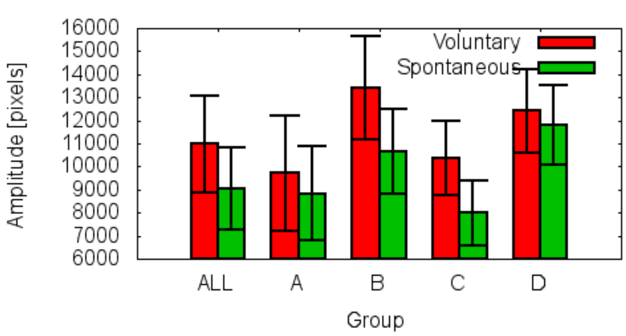

Fig. 9. Amplitude difference in every group.

VI. CONCLUSIONS

The study examined trends in the difference between voluntary and spontaneous eyeblinks based on shape feature parameters of subjects, attempted to solve the common problem of automatic classification of eyeblink types, and implemented an eyeblink input system.

As a result of conducting a shape feature parameters extraction experiment using 50 human subjects, a tendency in individual variation of differences based on the defined parameters between voluntary and spontaneous blinks occurred as follows: a significant difference in eyeblink durations was found in 24% of the subjects. For eyeblink amplitude, the difference was discovered in 22% of the subjects. For both parameters, the difference appeared in 46% of the subjects. Finally, no significant difference was seen in 8% of the subjects. In other words, a significant difference in the shape feature parameters between voluntary and spontaneous eyeblinks was seen in at least 92% of the subjects. Thus, the automatic classification of eyeblink types is possible using shape feature parameters in which significant differences appear in subjects.

A future study will aim to develop a real-time classification algorithm of eyeblink types and implement a real-time eyeblink input interface.

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