
Eye Blink as an Input Modality for a Responsive Adaptable Video System

Benjamin Tag

Keio University
Yokohama, Kanagawa, Japan
tagbenja@kmd.keio.ac.jp

Junichi Shimizu

Keio University
Yokohama, Kanagawa, Japan
jun.shimi@kmd.keio.ac.jp

Chi Zhang

Keio University
Yokohama, Kanagawa, Japan
nora.zhang@kmd.keio.ac.jp

Naohisa Ohta

Keio University
Yokohama, Kanagawa, Japan
naohisa@kmd.keio.ac.jp

Kai Kunze

Keio University
Yokohama, Kanagawa, Japan
kai.kunze@gmail.com

Kazunori Sugiura

Keio University
Yokohama, Kanagawa, Japan
uhyo@kmd.keio.ac.jp

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Abstract

We propose a unique system that allows real-time adaption of video settings to a viewer's physical state. A custom made program toggles between videos according to the average eye blink frequency of each viewer. The physical data is harnessed with J!NS MEME smart glasses that utilize electrooculography (EOG). To the best of our belief, this is the first adaptable multimedia system that responds in real time to physical data and alters technical settings of video contents.

Author Keywords

Eyewear; Smart Glasses; Activity Recognition; Eye Blink; Adaptable Video; Psychophysics

ACM Classification Keywords

Human-centered computing~Ubiquitous and mobile computing.

Introduction and Motivation

Content producers, technology companies, and distributors have constantly been looking for new ways to improve the quality of displayed contents since the birth of the first moving images. The digitalization of content production and the development of interconnected networks have created new distribution models for multimedia contents. In combination with the continuous evolution of production equipment and



Figure 1: J!NS MEME showing electrodes around the nose.

the simplification of production workflows the demand for highly personalized, new contents has grown relentlessly.

The system with the highest degree of individualization is, without any doubt, the human body. Within this system, our eyes take the role of gate keeper responsible for receiving and rejecting visual information. The endlessly available stream of information is naturally interrupted by our eye blink. Eye blinking is a necessary process for lubricating and cleaning the eye balls, but also to cut out visual stimuli, e.g. during times of rest and sleep. Blinking usually happens unintentionally, but can be controlled in situations where a delay might be crucial such as in moments of stress, fear, or danger [3].

Researchers at the University of Nottingham have been utilizing blinking for a film experience with their project #Scanners. The sequence of scenes of their movie is influenced by the viewer's eye blink and EEG [5]. Even though #Scanners allows every viewer to watch their own individual version of a movie, the production effort necessary for creating such a complex content structure is comparably high. Moreover, the constant scene cutting with every single eye blink tends to cause flustered experiences, especially for users with a rather high natural blink frequency (BF). This in return has an impact on the EEG and thus the actual experience.

A similar approach is taken by #AlmostForgot, a smartphone application that utilizes the user's heartbeat for adjusting the tempo of a piece of music. While watching an animated video, the user's heartbeat is measured with the phone's backside camera [1].

Our approach tackles the issue of customized content from a new direction. We are addressing the form before the substance, i.e. the technical characteristics before the actual contents (e.g. story) of a video.

Our Approach

Tag et al. investigated the impact of different frame rates (FR) on viewers' BF. Videos with 120fps, 60fps, and 30fps were shown to participants while their eye blink is logged with J!NS MEME glasses (Figure 1). The obtained results revealed a lower BF for higher FR video [6]. A different study by Kuroki has shown that our EEG patterns are closest to those of our natural EEG when we are watching video presented in 240fps. Therefore, it can be concluded that high frame rate video, which displays motion more similar to reality, causes less strain on the visual system of the viewer [4].

Build upon these findings, we produced a video that was rendered in 60fps (V_1), 30fps (V_2), and 15fps (V_3) respectively with appropriate retiming applied in order to avoid temporal distortions. We are currently using lower frame rates in order to keep the computational workload small, compared to a 30fps, 60fps, and 120fps system. As Figure 2 depicts, all three videos are simultaneously played, but only one is displayed on screen for the viewer. A Quartz Composer program toggles between these three videos. The eye blink data is input through a custom patch written for this program. Before showing the videos to the viewer, we let participants listen to music for some time while wearing the J!NS MEME smart glasses. During this time we log the natural blink, so that we can define every individual's BF baseline. The standard human BF is given with an average of 17 blinks/minute [2].

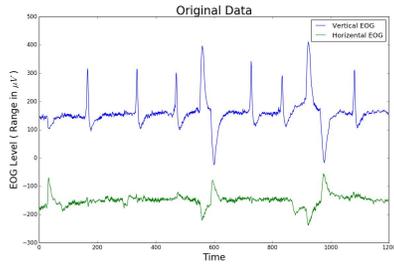


Figure 3: EOG Original Data, 6 blinks, 2 gazes up.

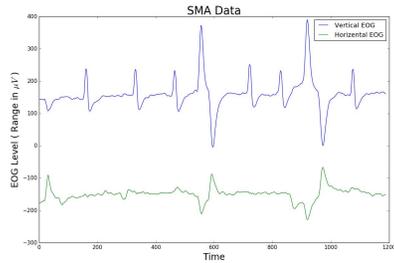


Figure 4: SMA Adjustment.

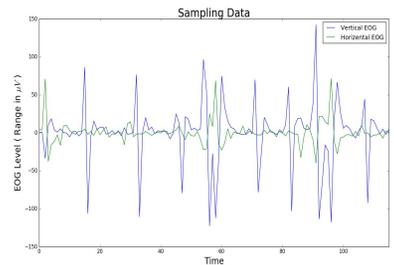


Figure 5: Comparison of sampled horizontal and vertical EOG values.

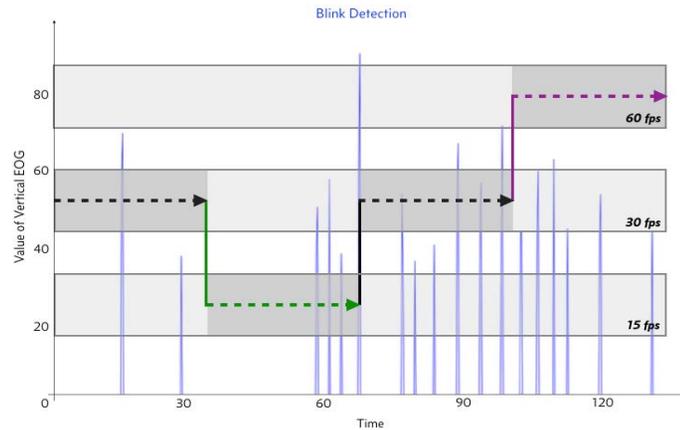


Figure 2: Schematic system algorithm. Variations in blink rate frequency over/under certain thresholds trigger video shift.

Nevertheless, natural characteristics, sleepiness, stress, monitor work, etc. cause every person to present with a different baseline frequency. After obtaining the baseline frequency (f_b) we input a lower (A) and an upper (B) BF threshold for every user. When BFs are going either over or under the respective thresholds the program switches to a different video. (A) and (B) are calculated with the following equations:

$$(1) A = f_b - (f_b/2) \qquad (2) B = f_b + (f_b/2)$$

The program constantly processes the input BF and toggles between V_1 , V_2 , and V_3 accordingly. In our setup every presentation starts with the standard frame rate video V_2 . If the BF goes below A the program will switch to video V_1 . The lower frame rate of V_1 will then trigger a higher BF. Since all three videos are synchronously played with the same speed and length, there are no leaps or glitches in the story.

To detect the eye blink we use off-the-shelf electro-oculography (EOG) smart glasses called J!NS MEME. Three embedded electrodes can detect the vertical and horizontal eye movement of the wearer. We implement a robust blink detection algorithm using these two values. The vertical and horizontal EOG data of a participant blinking six times and looking up two times can be seen in Figure 3. Due to the eye blinking relatively affecting the vertical EOG data, it is difficult to distinguish between an actual blink and a glance up. Moreover, the original EOG data is rather noisy. For extracting eye blinking data correctly, we adjust the SMA (Simple Moving Average) to 10 samples for each data set (Figure 4). We then sample 0.1 sec. and calculate the difference. After that, we sum up these values and compare the vertical and horizontal values (Figure 5). Finally, the eye blink can be clearly detected by setting a threshold for the vertical and horizontal EOG data (Figure 6).

Implementation and Future Works

The proposed mechanism proposes a new, unique video system that reacts to the physical state and perception of its users. It responds in real-time by adjusting settings for an individually tailored experience.

Responsive VR Graphics

Especially in virtual reality environments that require head mounted displays (HMD), it is of crucial importance to avoid overexertion of the visual apparatus. Blink rate frequency can be used to adjust the frame rate of the screens in the HMD to guarantee longer and less debilitating usage. Computational power can be used more efficiently and with the current generation of HMDs a wider range and finer tuning of frame rates is also possible.

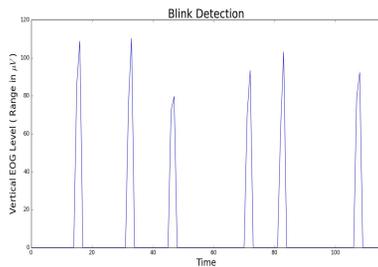


Figure 6: Detected eye blinks after setting threshold.

VDU-work

The proposed system is a simple but effective addition to today's predominantly existing screen-dependent work-, entertainment- and study environments. Less strain and exertion for the eye would mean more effective and healthier hours of work and pleasure.

Medical Applications

Medical Monitors can adapt to the individual characteristics of each physician and therefore make camera supported surgeries and diagnoses safer by taking physical stress off of the doctor.

Cinema/Video Therapy

Physical data can be used to understand the viewer's emotional state, and video settings can be adjusted accordingly. Thereby, certain emotions can be addressed more effectively, and the occurrence of overly stressful situations can be avoided. We furthermore believe that an adjustable multimedia therapy is able to help with the treatment of stress and burnout related conditions by fostering meditation in more relaxing environments.

Prospectively, the physical data used can be extended by data obtained from facial skin temperature (cognitive load), galvanic skin response (emotional response), and electrical brain activity (e.g. attention). This will allow researchers to draw more complex pictures of the users' physical and emotional state.

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