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Master's Thesis
Academic Year 2019

Introspectacles : Introspection Using Smart EOG Glasses

Keio University
Graduate School of Media Design

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A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Aman Gupta

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Abstract of Master's Thesis of Academic Year 2019

Introspectacles : Introspection Using Smart EOG Glasses

Category: Science / Engineering

Summary

The human eye has proven to be an enigma; a rich and complex organ that has not quite been fully understood. Naturally, this has caused the eye to be the subject of several medical and anatomical research efforts. More recently, the engineering community has used the eye as the inspiration behind the design and development of cameras, machine vision algorithms, and much more. In order to better understand the eye and its underlying patterns, the technique of electrooculography (EOG) was developed, in which electrical signals originating from the extraocular muscles are measured. The development of EOG has recently opened a new line of research within the engineering disciplines, due to its potential use as an input mechanism for computers and software applications.
In this thesis, I use a pair of Jins Meme glasses, a lightweight and commercially available EOG system, to investigate the potential uses of EOG within the realm of Human empowerment research. I tried to study two aspects of human behavior i.e, Individual and collective. For the individual aspect, weather we can detect fatigue level throughout the day of a person. For collective aspect, we try to answer how people interact with head/eye motions while having a conversation. In doing so, I find optimistic results — 1)Our proposed method allows for unobtrusive and continuous monitoring of alertness levels throughout the day,2)Our initial results on 18 dyads show significant effects of interpersonal synchrony of blink and head nod behaviour during conversation, and Japanese speakers are more likely to move (nod) together at fast frequencies (1 to 8 Hz) than non-Japanese. The development of innovative wearable technologies has raised great interest in new means of data collection in human empowerment research and development.

Keywords:

EOG Glasses, Jins Meme, Blink Detection, Fatigue Detection, Head Nodding, Social Interaction Analysis

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Chapter 1
Introduction

The human eyes can do more than just seeing the world, a rich and complex organ that has not quite been fully understood. the design of an eye has been a motivation for many engineering inventions like cameras, machines vision algorithms, and much more. Several studies has been done with the help of cameras recording the eyes continuously and process the video further for getting valuable signals such as blinks, saccadic movements etc. More recently, there has been a development of smart eyewear technology with affixed cameras in the frames, but they still need to be connected to a machine via wires for power and transferring the images. This leaves us with a bulky glasses which cannot be used independently and thus demands a much more conventional eyewear and techniques that can record eye signals thoroughly. In order to understand the eye and it's underlying patters, the technique of electrooculography (EOG) was developed, in which electrical signals originating from the extraocular muscles are measured. The development of Electrooculography (EOG) has recently opened a new line of research within the engineering disciplines, due to its potential use as an input mechanism for computers and software applications. In this thesis, I use Jins Meme glasses(Figure 1.1), a lightweight, compact and commercially available EOG system.

1.1. Introspection with Jins Meme

Understanding a person's activity is at the core of making wearable computing more personal and transparent. We have seen development in recognition technologies from physical activities(eg. daily step counting, differentiated assembly task analysis), over physiological signals(eg. heart rhythm analysis, breathing

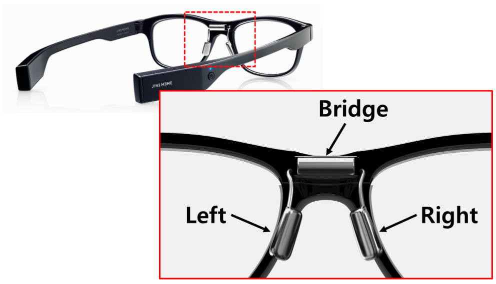


Figure 1.1 JINS MEME *EOG Electrodes*

rate), towards mental states and activities(reading detection, cognitive load). Jins meme,a compact device with sensors capable of detecting eyes, head and body motion opened doors for researchers to integrate the above technologies into the human lives. In my research, I focus on two aspects of applied cases in human lives:-Individual and social.

1.1.1 Individual setting : Fatigue detection

Humans have internal clocks which affect both their mental cognition and physical behaviour. The synchronization of our biological rhythm and the time-of-day can impact our cognitive performance [1], cause health problems [2, 3], and affect alertness and fatigue levels. *Homeostatic Process* (HP), increases the impulse to sleep with prolonged wakefulness [4]. It leads to an increased risk of making mistakes and thus higher chances of causing accidents [5]. These workloads are common in some professions, such as pilots and medical staff who work in shifts [6]. Furthermore, it is common to drive home after a full day of work, an increased risk due to high fatigue and sleepiness, where reflexes are delayed [7, 8] causing more severe accidents. Traditionally, alertness has been measured by constrained, unpleasant, or unnatural settings, such as in an enclosed and controlled laboratory, sleep labs, or through repeated measurement of body temperature through rectal probes [9, 10]. Due to the recent advancement in technology, it has made it much easier to measure and track various daily activities through smartphones, smartwatches, and wristbands. Physiological signals, such as heart-rate and blink rate are able to be collected without restriction on time or place. Such data has been shown to be able to detect and monitor different human cognitive states: Abdullah *et al.* [11] and Dingler *et al.* [12] have proposed mobile solutions for tracking cognitive capacities (*e.g.*, alertness) based on data from smartphones. One of the major downfalls of such studies and systems is that alertness measure are limited to when the phone is being used. There is a failure to collect data when driving, in social gatherings, or intense work sessions, and the phone is not being used. Additionally, interactions with the smartphone requires active engagement with it, drawing away from the actual activity users are engaging in and trying to analyse. To avoid such distractions which constrain the data, and to measure more reliably, I propose the use of technology which is unobtrusive and can continuously log data based on monitoring eye movements.

To enable people to accurately track their fatigue levels in their everyday lives(Figure 1.2), we propose a solution utilizing Jins meme to record EOG signals for detecting the characteristic eye movements occurring during eye blinks. Different studies have demonstrated that fatigue is directly related to changes in eye blink features, such as frequency and duration: greater fatigue causes higher Blink Frequency (BF) and longer blinks [13,14]. In this part of research, I use eye movement data collected via off-the-shelf Jins meme and use it to detect changes of fatigue.

Figure 1.2 fatigue detection with Jins meme

I along with researchers from Keio Media Design (KMD) collected in-the-wild EOG data to detect the changing fatigue levels in everyday situations:for two weeks, participants periodically completed self-assessments in the form of psychomotor-vigilance tests for providing ground truth while wearing Jins meme.I found a statistically significant, positive correlation between BF and Reaction Times (RTs) meaning that blink frequencies increase along with reaction times (*i.e.*, slower reflexes) over the day.

1.1.2 Social setting : Synchrony detection

Figure 1.3 Synchrony detection with Jins meme

In my research I am interested in capturing personal and interpersonal behavior with unobtrusive, affordable wearable sensing. In this section of my research, I focus on eye and head movement synchrony during dyadic, open conversation captured by Jins meme.

People tend to synchronize certain behaviors, but in some cases, e.g. autism, such synchrony is not always as obvious [15, 16]. According to Chartrand and Bargh, synchrony of nonverbal behaviour is a sign of greater empathy and more effortless interaction [17]. We require novel methods to measure these forms of synchrony in group interactions. I propose the use of smart eyewear to explore head and eye movement synchrony in free conversations and provide a first, public dataset with 21 communication pairs. The pairs engaged in different conversations while facing each other or sitting back to back. We recorded EOG and Inertial

Measurement Unit (IMU) from smart glasses they wore and additionally video and audio, and analyse the interpersonal synchrony using wavelet coherence analysis.

1.2. Contribution

The main contributions of this work are as follows:

- Approach and set of tools to analyze EOG and IMU data for introspection analysis
- A model which allows continuously recorded EOG data and the resulting eye blink frequencies to predict fatigue level changes in everyday settings
- In synchrony analysis, we find a low-frequency (0.1 Hz) interpersonal synchrony in eye blinks of people conversing face-to-face vs back-to-back. However, the strongest effect reveals that people conversing back-to-back synchronise their blinks more than face-to-face at frequencies around 1 Hz.
- In synchrony analysis, we show that statistically significant synchrony of head nods at a frequency of 1-8 Hz enables us to differentiate between English and Japanese conversation dyads.

Chapter 2
Background

The work presented here builds upon research from the field of EOG glasses(JINS MEME), cognitive psychology and interpersonal synchrony. The research consist of fatigue detection has been published in CHI'19 [18] and the work involving social synchrony has been successfully accepted in ISWC'19.

2.1. Eye data and Electrooculography

Eye movements and Electroencephalography (EEG) provides insights into mental states and behavior. [19, 20]. EOG sensors specially, records the electrical activity caused by the eye movements, which is utilized in this work to record eye blinks. Being highly flexible and depending on several environmental factors, human eyes blinks at an average of 15-20 times per minute [21]. Eye-blinking is not only responsible for lubrication of the eyeball but is also directly related to neural activities [22, 23]. Studies have shown that about one-third of our natural eye blinks are sufficient to fulfill the cleaning function [24], meaning that the remaining blinks serve a different purpose [25]. Nakano has found that when humans engage in social situations, especially relating to states of arousal, cognitive engagement, and emotional changes, their blink frequency change significantly [26].

Although EOG-based measuring systems have been successfully used for activity recognition in the past [27], but it required computing sensors to be attached to the face and connected with a computing unit through cables, which rendered the setup rather intrusive. A less intrusive way to measure this data would be to integrate EOG sensors into regular prescription glasses to track eye movements throughout the day in an unobtrusive way. EOG is immune to any form of light changes enabling eye movement measurements in well-lit (outside, daytime) as well as in dark environments (inside, nighttime). EOG utilizes the electrical potential difference between the cornea (+) and the retina (-), that change when the eyes move. When closing the eyelid during a blink, eyes perform a characteristic downward oriented motion that can be measured by electrodes correctly placed around the eyes and nose [28]. EOG offers an effective and low-power solution to monitor intricate eye movements, making it ideal for measuring daily life in long-hours. It can also be used as a input modality for HCI and ubiquitous computing applications [29, 30].

2.2. Fatigue detection with eye data

Blink rates increase with fatigue, along with eye movement speed decreasing and blink duration increasing [31]. Recent works, such as by Haq *et al.* [32] present highly accurate methods to detect eye blink rates of drivers indicating drowsiness and fatigue levels. While the application case is limited to the user being in front of the stationary camera setups, the necessary image processing, and computer vision algorithms [33] require considerate computational complexity [34]. Less cumbersome setups are made possible by mobile systems, which often rely on commercially available head-mounted infrared cameras installed in eye trackers [35] or on infrared reflectance sensors [36]. While the utilized bright infrared light bears an inherent risk of irritating the eye through the emitted heat if not properly set up, different works have also shown that these systems are likely to produce faulty measurements because of changing light conditions [37, 38], rendering their in-the-wild use as not feasible.

With the technique presented in this research to unobtrusively and frequently measure alertness levels throughout the day, I aim to advance the development of systems that become cognition-aware [29, 39, 40].

Such systems are capable of adjusting user interfaces to the user's current cognitive capacities, therefore avoiding frustration and boosting productivity levels [41].

The tracking method presented in this research provides a gateway capable of measuring a user's cognitive state through continuous assessment of alertness levels in an unobtrusive manner.

2.3. Social behavior with eye data

This section discusses the underlying psychology research related to head nodding and blink synchrony in conversations, followed by the field of social sensing, dealing with unobtrusive sensing devices to capture human behavior.

There is a lot of applied psychology research looking into head and eye movement related to conversation [42–44]. Tschacher et al. find a link between interpersonal synchrony and affect using nonverbal movement energy from videos [43]. Hale et al. provide insights into interpersonal coordination in naturalistic conversations [44]. They show interpersonal synchrony of head nods in dyadic conversation. Listening behaviour is associated with higher frequency nods. Dittmann et al. observe that nods, blinks, and vocalisations are used by the listener during breakpoints in speech [45]. Ward et al. sense interpersonal synchrony between actors and autistic children in theatre using wrist-worn accelerometers. It is the first use of cross-wavelet based measure for assessing interpersonal engagement using wearable sensing [16]. Nakano et al. show the lack of eye-blink entrainments in autism spectrum disorders [15]. And Homke et al. explore the way in which subtle changes to eye-blink in virtual agents can affect the way in which people interact with them [46]. They suggest that eye-blinks are a useful nonverbal signal of listening behaviour.

There are similar studies focusing on cultural differences in interpersonal behavior. Szartowski et al. show that English speakers expect the listener to look at them at the beginning of a speech segment. Japanese speakers expect a well-time head nod at the end of speech and aizuti, frequent interjections during a conversation that indicate the listener is paying attention [47]. Maynard et al. explore head movements changes during conversations between Japanese and Americans. The head nods are 3 times as high for Japanese as Americans in listeners. In both, listeners use head nods indicating to speaker to continue. Yet, Japanese use head movements to indicate end of clauses, turns, and agreement; English use head movement as emphasis [43].

These studies provide the theoretical basis that this research builds on, as the evaluations are more obtrusive lab experiments, often using manual analysis of video or audio data. I strive for unobtrusive, automated analysis (and ultimately real time feedback).

My research is connected to the field of Social Sensing, utilizing affordable sensors to enable the unobtrusive capture and interpersonal behavior analysis [48]. I follow the pioneering work of Choudhury and Pentland, who developed the Sociometer Badge [49]. The badges can capture audio, which other badges are nearby and motion information with the purpose of building computational models of group interactions. Shmueli et al. present a comprehensive summary on the topic [50]. Gordan et al. added the direction of collaborative activity recognition for group activities [51]. The head nodd as an important communication clue is also addressed in several tele-presence focused publications. For example, Madan et al. transfer remote users head nodding behavior in real time for group discussions [52]. A lot of social sensing work applies either static computer vision approaches or use pocket worn devices (e.g. mobile phones) [53–55]. There are of course limitations especially regarding synchrony measurements, as the placement of the devices is not fixed on the body.

To uncover synchrony between participants, we use a method based on wavelet coherence analysis. This is a method of highlighting correlations in both time and frequency between two signals, and was originally developed to measure co-variations in weather patterns [56]. Wavelet coherence has been used to reveal how people synchronise with one another at specific frequencies of head movement in dyadic conversation [44, 57]. Whereas previous work used video and motion capture, my work introduces a first attempt to apply coherence analysis to conversation data obtained from two different head-mounted sensors (EOG and IMU).

Chapter 3
Implementation

In this section, I will describe how Jins Meme can be used to detect fatigue levels of a person and synchrony level among two people in a conversation. Since there has been no past development of fatigue detection and social synchrony with Jins meme, I present the prototype implementation and sophisticated approach for doing such analysis with EOG data from the glasses.

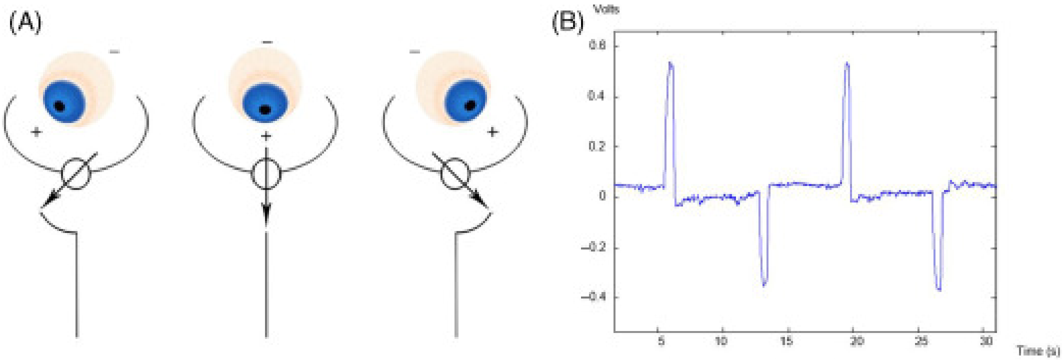
3.1. Apparatus

To create an efficient system, it is important to check the working process and limitations of the technology. Here I explain about EOG and Jins Meme and their limitations.

3.1.1 Electrooculography (EOG)

Electrooculography is a method for sensing eye movements. The electric potential arising from hyperpolarizations and depolarizations between the cornea and the retina causes this phenomena; this is commonly known as an electrooculogram (EOG).

This potential can be considered as a steady electrical dipole with a negative pole at the fundus and a positive pole at the cornea (Fig- 3.1A). The standing potential in the eye can be measured by the voltage induced across a system of electrodes placed around the eyes as the eye-gaze changes, hence obtaining the EOG (measurement of the electric signal of the ocular dipole).



(Source: Science direct [58])

Figure 3.1 (A) Ocular dipole, (B) EOG signal obtained from horizontal (right–left) eye movement.

3.1.2 Jins Meme

Jins meme are eyeglasses sold in Japan. These glasses are equipped with EOG sensors around the nose, in addition to an IMU (accelerator and gyroscope) around the frame(Figure 3.2 A). It can log data to Android phones via the J!NS Bluetooth LE (low energy). With a maximum sampling rate of 100Hz, the glasses stream 10 datapoints (3 ACC, 3 GYRO, 4 EOG) at a time. To calculate EOG values, the J!NS follows the formula shown in Figure 3.2 B.

There are some limitations with this device, which changed the approach of studies done with it in the past. Since EOG is an electrode based sensor, it is required to have non interfering contact with the skin during the study. Hence most of the studies done in the past are done in a static environment. In this thesis I present an approach of analysis for the noisy data collected in the dynamic environment during the fatigue study.

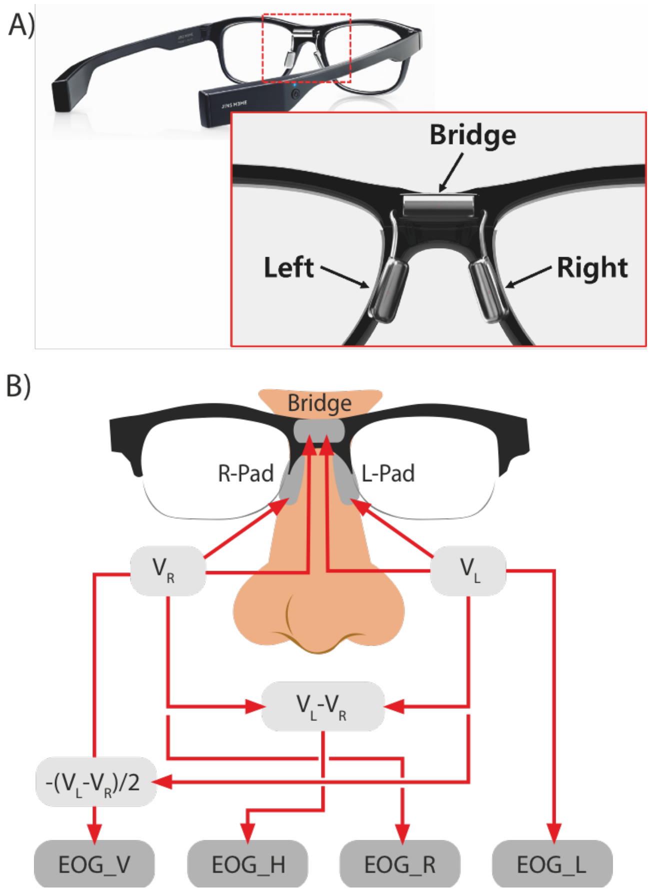


Figure 3.2 A)Sensors in Jins meme B)Calculation of EOG values from raw data of Jins meme

3.2. Data collection

To collect data, a user needs to wear the glasses while doing the study. The glasses connects to a mobile device via Bluetooth and streams data continuously when started. Jins provided an application called 'datalogger' to work with the academic version of the glasses. It comes with a Graphical user interface (GUI), via which a recording can be initiated and stopped. It also allows to see the real time graph for EOG and IMU values on the mobile device. The data stream stores as a .csv file in file system of the mobile device once it is stopped via GUI.

see Figure 3.3 for data collection process.

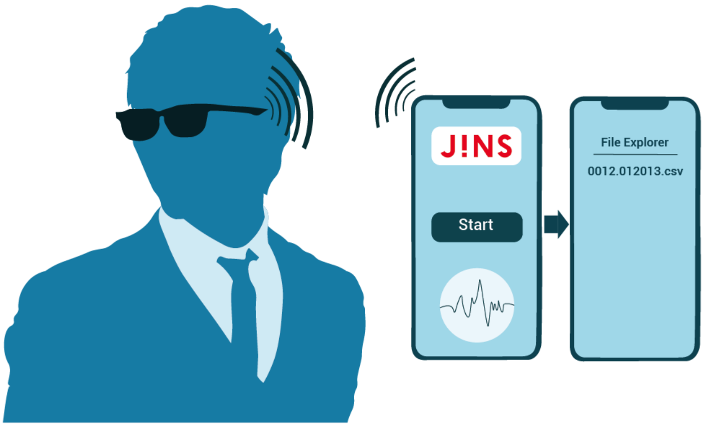


Figure 3.3 System overview

A typical csv file looks like shown in the figure 3.4. The timestamps in the file

NUM	DATE	ACC_X	ACC_Y	ACC_Z	GYRO_X	GYRO_Y	GYRO_Z	EOG_L	EOG_R	EOG_H	EOG_V
1	2019/04/18 04:17:05.12	14470	4238	-5455	16	-66	-37	-131	-40	-91	85
2	2019/04/18 04:17:05.13	14364	4275	-5376	10	52	-7	-135	-33	-102	84
3	2019/04/18 04:17:05.14	14360	4327	-5380	16	-13	-45	-150	-33	-117	91
4	2019/04/18 04:17:05.15	14343	4331	-5435	10	-93	-13	-165	-31	-134	98
5	2019/04/18 04:17:05.16	14402	4359	-5470	-4	106	3	-165	-37	-128	101

Figure 3.4 A typical csv file recorded in 100 hz

are UNIX timestamps which match the universal epoch time, we later use these for synchronisation of two devices.

Since in this thesis, I explain two aspects of introspection, I divide the further explanation and analysis into two parts-

3.2.1 Individual

I collaborated with researchers from KMD, and we collected EOG data to investigate the correlation between EOG and blink frequencies.

Participants

Participants in this study were recruited from university and our social network. We got 16 participants(7 female), with an average age of 28 years.The participants had no eyesight issues and were not taking any fatigue related medicines. In the end of the study, they were paid 3,000 yen each as compensation.

Procedure

We had one-on-one interview with the participants in our lab, where they were given a brief introduction about the study. This was a 14 day study and people had to wear the glasses throughout the day from morning till sleep.The glasses could be taken off when a user is doing water related activity like shower or swimming. Every morning they had to connect the glasses to the Jins mobile application and disconnect at night. Since Jins states that a fully charged device can run upto 14 hrs flawlessly, the users had to charge the device overnight to avoid cases of battery run out in between study.
Together with the Jins Meme devices, we handed out android smartphones to our participants, which recorded the EOG data as well as contained and triggered self-assessments every two hours ($\pm 20 minutes$). We adapted this mobile toolkit by Dingler *etal.* [12] to collect our ground-truth data. The toolkit based on Android features a task battery enabling the assessment of alertness and different higher cognitive functions. Since the Psychomotor Vigilance Task (PVT) has been shown to provide the greatest amount of data points and most accurate alertness measures, we limited assessments to this one and left out the other two task types provided. After every self-assessment, the PVT begin with 10-15 rounds with random delays of 2-8 seconds between visual stimulus onsets resulting in test lengths of 20-120 seconds plus the individual RT for each round. The User Interface (UI) of the assessment app is shown in Figure 3.5
Later on we used the EOG data collected in the study to find the blink frequencies

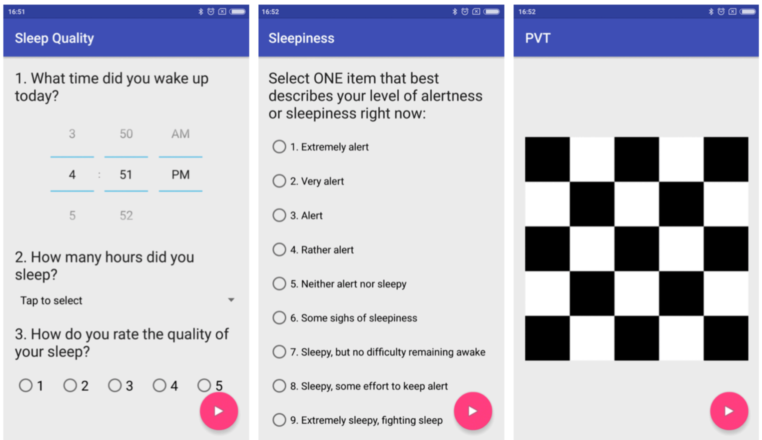


Figure 3.5 Android Application functions from left to right:daily sleep assessment, alertness self-assessment on the Karolinska Sleepiness Scale (KSS), and Psychomotor Vigilance Task (PVT) assessing reaction times

and used the PVT values as a ground truth of fatigue.

3.2.2 Dyadic

To study the eye and nod synchrony while having a social conversation, I collaborated with researchers from Goldsmith University and KMD. We collected EOG and IMU data from Jins meme, followed by separate video and audio recordings.

Participants

This study was done in a relatively static environment compared to the fatigue study. Participants were recruited from the university. In total we got 42 participants (21 dyads: 10 in Japanese, 10 in English, 1 in Chinese) engaged in conversations (face-to-face and back-to-back, in total 17 hours).

Procedure

In this study, pairs of participants were asked to have two conversations on two assigned topics. Participants had one conversation facing each other (FF) and one conversation sitting back to back (BB) so that they were not able to see the other

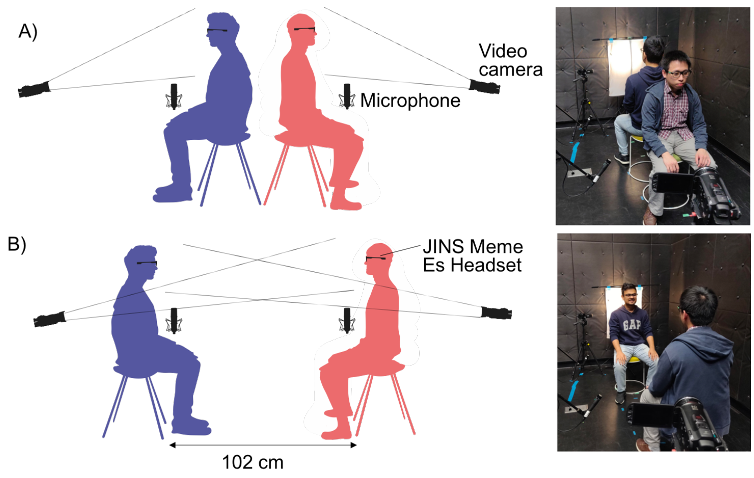


Figure 3.6 Experimental setup. Participants had one conversation back to back (A) and one conversation face to face (B). Audio and video recording directionally captured both conversations.

person (3.6). Each conversation lasted for five minutes. When facing each other, participants sat 102 cm apart, a comfortable distance for Japanese seated dyads, the largest demographic in our experiment [59]. When facing away from each other, dyads were seated close together so that they could easily hear one another without touching. The first conversation topic was to "come up with a four-course meal that you could cook with your partner, using only ingredients that neither of you like". The task was adapted from Chovil [60] and Tschacher [43]. The second conversation topic, devised to imitate the first, was to "plan one day of a holiday you could take with your partner, only doing things that neither of you enjoy doing." Conversation topics were described to participants directly before the beginning of each conversation. The direction faced for the first conversation was alternated throughout the study, and the two conversation topics were used equally facing both directions.
The EOG and IMU data was later used to find the synchrony among the dyads.

3.3. Data analysis

After collecting extensive amount of data, an appropriate approach has been followed for a given problem. In the following subsections, I described a follow up approach for filtering and further analysis.

3.3.1 Signal filtration

EOG signals collected via Jins meme are prone to a variety of noises and need to be filtered. Majority of them are:-

- Baseline Wander
- Power-line interference
- Motion artifacts

Baseline wander and power-line interference are both low frequency noise in nature.They are mainly generated by electrode-skin impedance and the electromagnetic field of the hardware respectively. They can be removed easily from the signal via an inbuilt low band-pass filter in Python's Scipy library. On the other hand, motion artifacts are hard contamination in the signal [61] which are generated mainly because of the electrode motions away from the contact zone on the skin. In the wild data collected from Jins meme have a higher possibility of having motion artifacts, and hence creates many false positives and negatives during our analysis.

3.3.2 Blink detection

After the removal of noise, a typical EOG plot looks like Figure-3.7. It can be seen from the figure that spikes in the signal are very similar to each other in nature and can be recognized easily with modern analysis techniques. In the EOG Vertical data, these spikes represent the eye blinks of a person.

To estimate the eye-blink, a moving window of step size 0.25 sec is iterated over the signal and a thresholding technique is used to detect the pattern of blink(Figure- 3.8).

Following conditions are followed in the algorithm while detecting the blink pattern inside the moving window.

```
Amplitude of maxima > threshold_1
Distance between maxima and minima < threshold_2
X Position of maxima < X position of minima
```

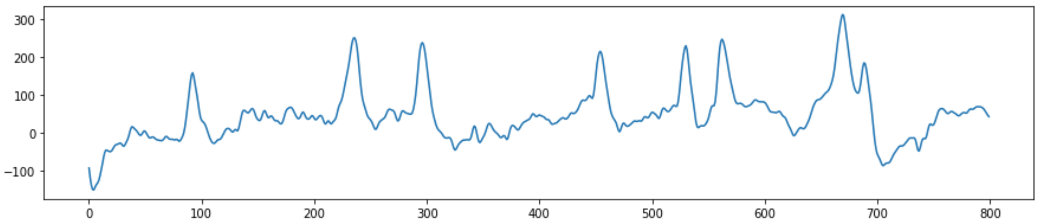


Figure 3.7 Raw EOG data for 8 sec, where a person blinked 7 times

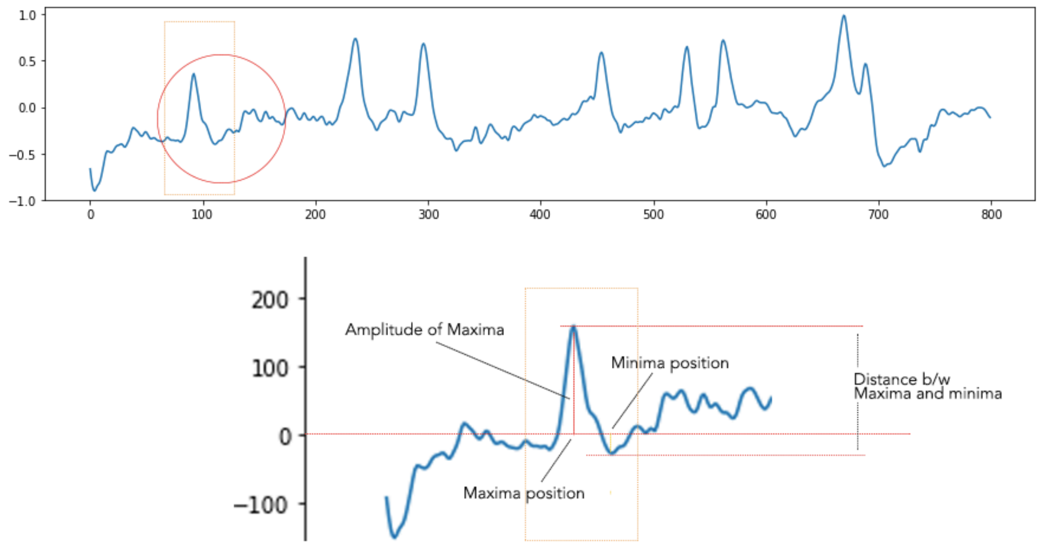


Figure 3.8 Moving window and parameters used in Blink detection algorithm

Since eye blinks are characterized by a maxima followed by a minima, the algorithm uses two thresholds *threshold_1* and *threshold_2* to detect blinks. *threshold_1* describes the height of the positive peak, i.e. the amplitude of the maxima, and *threshold_2* describes the vertical distance between both peaks, i.e. the vertical distance between the maxima and minima. These threshold varies from person to person, as their electrical response of ocular muscles may vary. Due to the dynamic nature of thresholds, It is required to check a person's data manually and find the thresholds by peak detection.

threshold_1	threshold_2
0.8	2

Table 3.1 Best thresholds matching with the validating blinks

After checking the data of 16 people and also referring to the blink validation data we collected ourselves, the best results were coming for thresholds given in table- 3.1.

3.3.3 Wavelet coherence analysis

For comparing EOG and IMU data of two people, a more powerful and universal processing tool than thresholding is needed. Wavelets enable us to decompose a signal into its frequency components while preserving temporal information, and without the need for windowing and thresholding [62]. Obtaining the wavelet transform from two signals and then combining the outputs provides a way of obtaining the common time-spectral response. Two related methods of combining these include the cross-wavelet transform, which highlights the frequencies with high common power, and the wavelet coherence transform, which highlights common frequencies regardless of power [56]. Here I use wavelet coherence because of its superior performance on subtle, lower-power data.

The wavelet coherence spectrogram is obtained by combining wavelet spectrograms of the two signals being analysed (one from each of the conversing participants, here referred to as left, L and right, R). This process is shown using EOG-V for a 6 s sequence of two people conversing in Figure 3.9. The wavelet coherence spectrogram (for both EOG-V and ACC-Y) is obtained in 3 steps:

- Low-pass filter the raw signals for L and R (5th-order Butterworth, cut-off 20Hz)

- Apply a continuous wavelet transform to the signals, W_L and W_R,
- Calculate the cross-wavelet transform by multiplying W_L by the complex conjugate of the other W_R^*, i.e. $W_{L,R} = W_L * W_R^*$, and then normalising for signal power to obtain the wavelet coherence (see [56] for full details).

The wavelets used in this work are calculated using the continuous wavelet transform function from the PyCWT module in Python (with Morlet base).[1]

Wavelet coherence spectrograms were computed for all the EOG and IMU data signals between conversing partners, and the results averaged for each condition over time to give a typical frequency response. Here we present only the data from vertical eye movement, EOG-V (blink), and y-direction acceleration, ACC-Y (head nods), as these are the most relevant signals to the current study. The frequency response is represented by the approximate wavelet scale periods, or $1/frequency$. Paired t-tests (with p=0.05, N=18) are applied across all of the conditions explored below (except the cultural comparison with N=16). To account for multiple comparisons, Benjamini-Hochberg FDR correction is also applied (at 0.05).

1 https://github.com/regeirk/pycwt

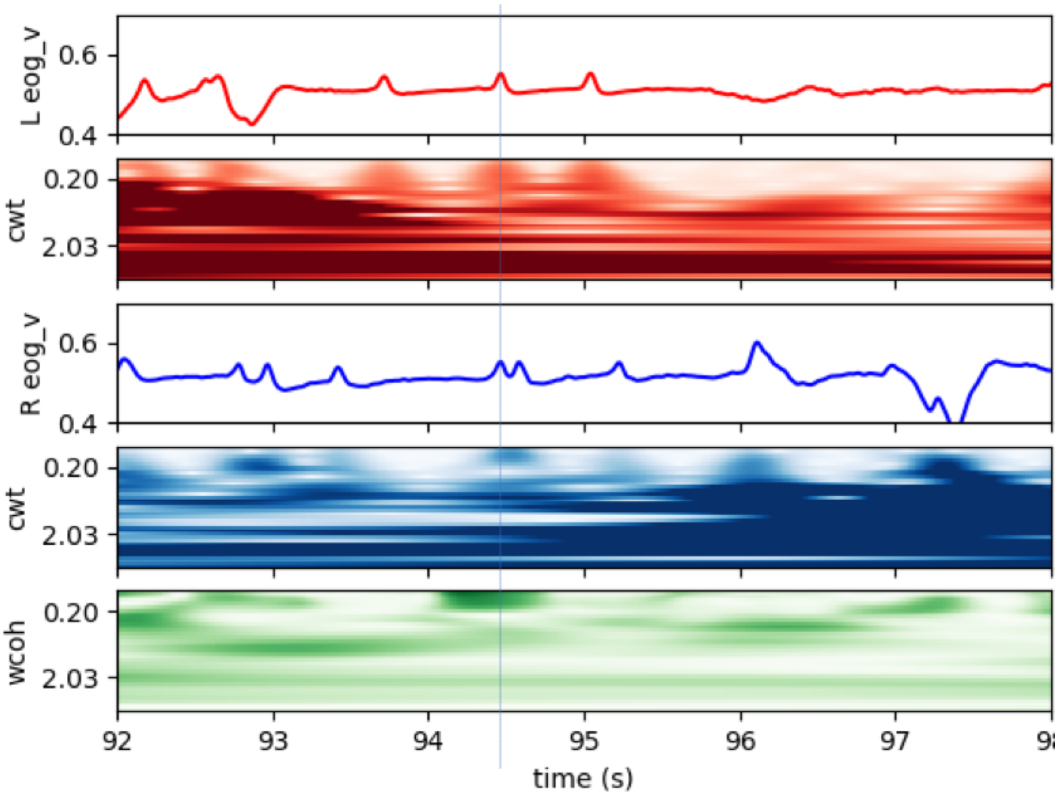


Figure 3.9 6 sec example conversation (dyad 12, BB, Japanese). Raw EOG-V signals shown, with corresponding continuous wavelet transforms (cwt) for each, and the resulting wavelet coherence WCOH spectrogram from combining these. Darker regions on the spectrograms show higher power/coherence values. Dotted line shows a moment of sychronous blinking and resulting wcoh (at scale of approx. 0.2 s).

Chapter 4
Results and discussion

4.1. Fatigue detection

The goal of this study was to establish a relationship between eye blink frequency and fatigue changes throughout the day. Therefore, we needed to co-relate the ground truth, *i.e.* changes in RT to the blink frequency.

After getting data of 16 participants over a course of 14 days, the total of 2860 hours of raw EOG data was logged. On the course of this period, the participants responded to an average of 4.09 ($SD = 2.01$) assessment tests per day, which accounted for an average of 65.44 ($SD = 28.1$) assessment test per person, with a minimum of 24 assessments and a maximum of 115 assessments, resulting in a total of 1,047 PVT assessments.

Assuming an average of 16 wake hours per person and day, this would result in approximately 8.5 hours of EOG recordings per person and day. In order to be able to identify correlations between the blink frequency and the reaction time, a 10-minute period of EOG data that directly preceded the respective assessment test was analyzed. This time window prior to the assessment test was chosen to avoid potential effects resulting from performing the PVT.

4.1.1 Correlation Analysis

After running the blink detection algorithm, I fit a linear mixed model to the raw data with the RT obtained from the PVT readings as the dependent variable and BF. The participating users were treated as a random factor. We use the time codes of the PVT recordings to identify the times of assessments and extract the 10-minute EOG data segments that precede each assessment test. Pilot tests with different window sizes showed that the 10 min window yielded the best

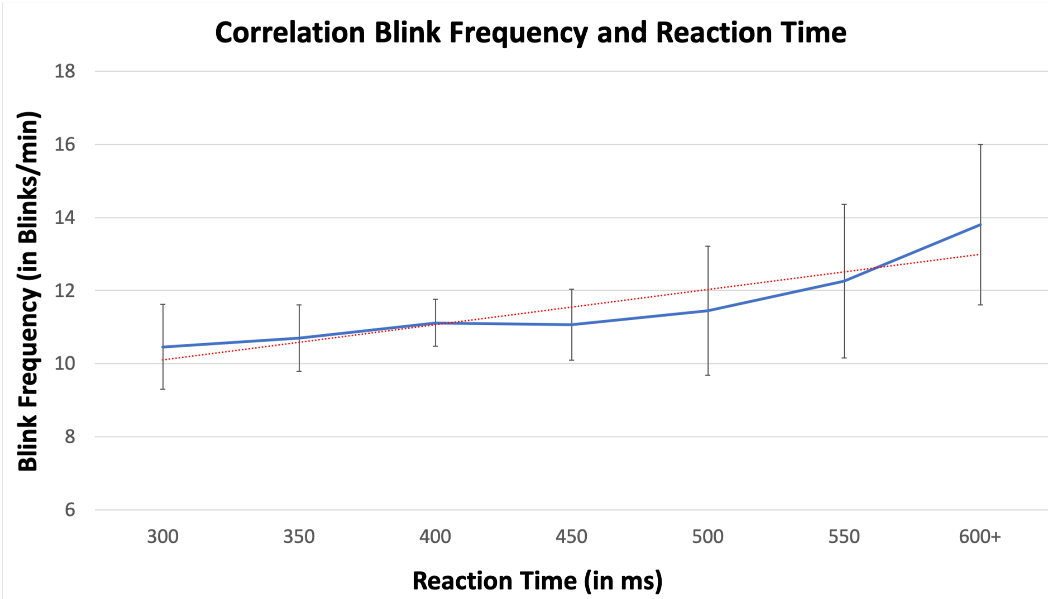


Figure 4.1 Visualization of correlation between blink frequency and reaction time (blue line). Linear trend is expressed in red line.

results as it is sufficiently large to collect a reasonable amount of data and small enough to still resemble a current, cognitive state. We removed 324 segments that did not contain any data, deriving from hardware issues, leaving 623 segments of valid EOG data. The 623 analyzed EOG segments yielded an average blink frequency of 11.4 blinks/min ($SD = 12.7$). Our analysis shows that BF changes with RT ($\chi^2(1) = 4.32, p = 0.001$), expressed in an increasing RT by about 1.64 milliseconds ± 0.38 (standard error), and BF of +1 blink/min.

We corrected for multiple comparisons by using the Holm-Bonferroni method. The model was validated by a robust linear model which accounted for the effects of outliers. The results were similar, and the significant factor was retained. The results show that BF is an indicator for fatigue expressed in changes of RT (Figure 4.1, which coincides with the related literature [21, 22].

4.2. Social interaction

We performed evaluations to test 2 hypotheses: 1) people synchronise nods and blinks during conversation, 2) people synchronise differently when they can see one another vs when they cannot. We also explored the cultural differences between Japanese speaking vs. non-Japanese speaking participants (English speaking, although not native).

4.2.1 Do people synchronise in conversation?

Coherence data from real conversations are compared against coherence data from pseudo-conversations. Pseudo conversations approximate a random interaction using signals from two people who are not actually in conversation with one another. To calculate this, we calculate the coherence of, say, person L during the FF condition, with their partner, R, taken from the BB condition, and vise versa. By comparing real-vs-pseudo we can uncover synchronicity that occurs in actual conversation as distinct from just the combination two individuals speaking.

Figure 4.2 shows our main result, which confirms the hypothesis that people synchronise with one another both in eye blink, and in head nod. The effect is particularly strong at periods greater than 2 s – suggesting a relationship to the dynamics of speech prosody.

4.2.2 Do people synchronise more face-to-face than back-to-back?

The right plots on Figure 4.3 suggest that there is generally no significant difference between conversants' ACC-V when face-to-face (FF) vs. back-to-back (BB). However, when analysing EOG-V (the left plot), a significant difference is found in favour of BB at interaction periods of around 1 s (1 Hz). This surprising result suggests that people coordinate blinks more when they cannot see one another. Why this is so is not clear. Is it, for example, related to entrainment of breathing patterns when people who are sat next to one another and talking, but cannot see one another?

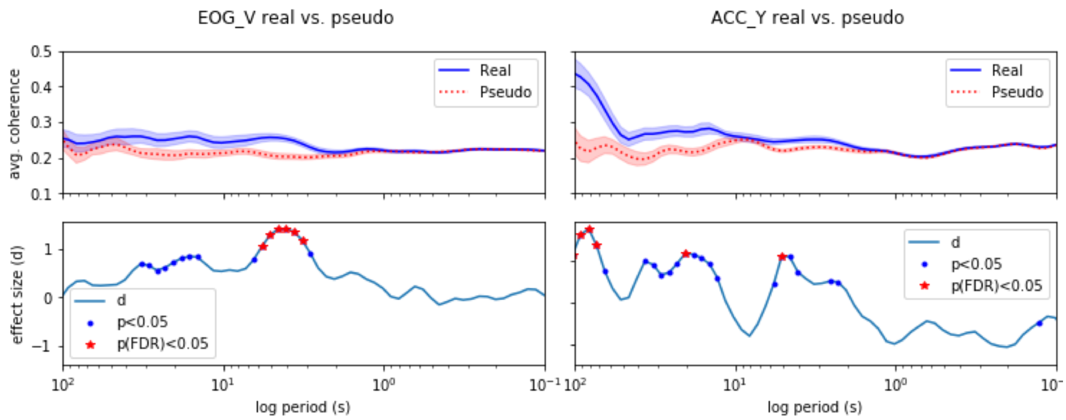


Figure 4.2 Real conversation vs. pseudo for blinks (EOG-V) and nods (ACC-Y). Average coherence for each condition is shown (with standard mean error, SME in the shaded regions). Effect size (Cohen-d) is also shown with significance levels highlighted. This shows 1) we synchronise our blinks at periods of greater than 2s during conversation, and 2) we synchronise head nods over these same (low) frequencies.

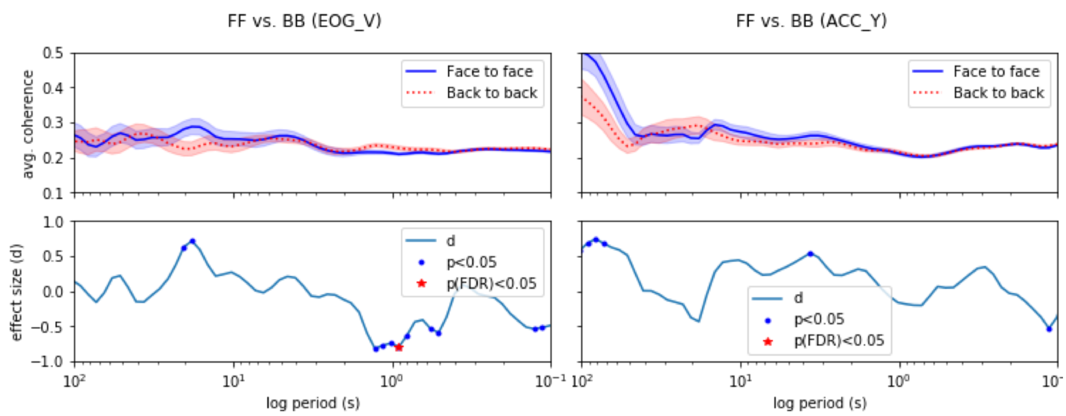


Figure 4.3 FF vs. BB conversation for EOG-V and ACC-Y. This shows 1) much of the synchrony in both nodding and eye blinks occurs irrespective of whether people are face-to-face or not, 2) and people synchronise their blinks at periods of 1 s more when back-to-back.

4.2.3 Do different language groups synchronise differently?

In the Japanese vs non-Japanese comparison (Figure 4.4), 2 additional pairs of Japanese are excluded to ensure a balance between groups. Here we find no significant difference for EOG. However, there is evidence for fast synchronised nodding behaviour being more likely among the Japanese participants than the non-Japanese. Interestingly, at long periods (10 s, possibly turns in conversation), non-Japanese will synchronise their nods slightly more.

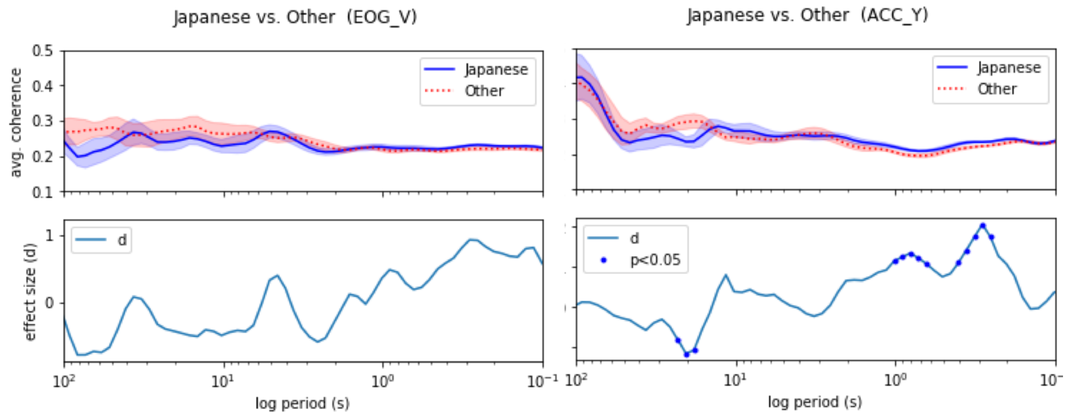


Figure 4.4 Japanese vs non-Japanese conversation. No significant difference between Japanese and non-Japanese for EOG-V. But ACC-Y suggests that Japanese speakers are more likely to move (nod) together at fast frequencies (1 to 8 Hz) than non-Japanese.

4.3. Discussion

One limitation of using the EOG glasses for the introspection study is their exposure to noise. Since the EOG sensors are electrode based sensors and it is very easy for them to loose contact with the skin, this results in the hard muscle artifact noise. when participants touched their faces or were turning their head rapidly and even when they used their facial muscles intensely, the EOG signal became too noisy, likewise observed by Rostamina *et al.* [34]. Removing the noise from the dataset and finding the right thresholds for every user to detect blinks properly was challenging. Additionally, even though we tested every glasses-phone connection several times before the study, random disconnects lead to the removal of ground truth data from our dataset.

As blink duration is also directly related to fatigue [13, 14]. An analysis for changes in blink duration has not yet been included in the research. Whereas Bulling *et al.* [27] managed to accurately detect blink durations with a 128 Hz sampling rate, the available rate of our off-the-shelf device leaves the collection of data and subsequent analysis of blink duration changes for future work.

Blink synchrony has been related to turns of speech, which our data supports [15, 44]. However, we show -for the first time- this synchrony can be detected using unobtrusive, affordable wearable sensing. Equally, visual and motion-capture sensing of nod synchrony at these lower frequencies has been reported, but which we now confirm can be captured using inexpensive smart glasses [44]. Our analysis also reveals some cultural differences in these signals between Japanese and Non-Japanese conversations. Additionally, there are interesting novel insights that are not explained by social psychology works (e.g. users synchronise at 1Hz when conversing back-to-back). We are also looking forward to findings from other researcher community using and building our dataset. The technique used in synchrony analysis can not only be used with EOG or IMU data, but can be used with signals of any repeating sequence, Hence expanding the area of synchrony study.

Chapter 5
Conclusion and future works

In this section, I present the conclusion and the future works.

5.1. Conclusion

I presented Introspection with the help of EOG glasses in both individual and social setting. For individual setting, I showed the feasibility of eye blink frequencies to detect the fatigue level throughout the day. For social setting, I showed how EOG data can be used in studying synchrony by finding head nodd synchrony in different cultural groups. For fatigue analysis, I used blink detection algorithm based on amplitude thresholds. While for synchrony analysis, I used wavelet coherence to find how synchronised two signals are. The performance of both the setting were evaluated and we found significant statistical proofs of our hypothesis.

5.2. Future works

Since we recorded video and audio data in the social setting research, I analysed the video data further and was able to detect facial landmarks(see Figure- 5.2 for reference) with the help of openCV.

As seen in the figure 5.2, the facial landmarks are represented as points. looking at the eyes we have an eye landmark made of 6 points and mouth landmark made of 20 points. Since these landmarks are accurate and not susceptible to noise, we can rely on these data to detect the accurate blink time and speaker detection.

For the future work, the eye blinks detected via facial landmarks will be used

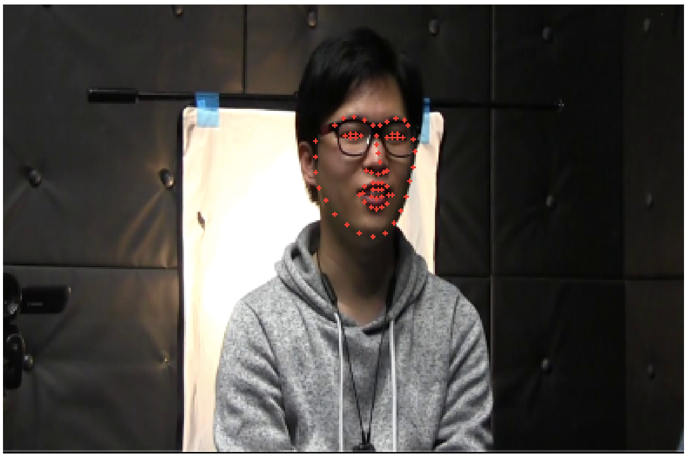


Figure 5.1 Facial landmarks including eyes, mouth, nose and jaw

as a training dataset to train a machine learning model with the sole purpose of detecting blinks from the noisy EOG data. and the landmarks from mouth can be used for detecting speaker in the study. If successful in that, then more interesting analysis can be done with the cultural dataset.

For application scenarios, we make further steps towards unobtrusive cognition-aware systems that enable us to detect complex contexts in everyday situations. we can use the insights of this research to build a personal log of face-to-face communications throughout the day and even include cultural peculiarities about that conversation (maybe language or category). Furthermore, these findings can help to make more realistic AR/VR avatars and mobile robotic assistants capable of coordinating head/blink synchrony with the user. They can engage better by adapting to unique cultural features like the different head nodding behavior in Japanese conversations.

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