Does Self-View Mode Generate Video Conferencing Fatigue? An Experiment using EEG Signals

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Abstract. The ability to see or hide one's own image is a typical feature of video conferencing platforms. This study will conduct an EEG-based neurobiological experiment to determine if the self-view mode generates video conference fatigue and if this differs between males and females. 40 volunteers will participate in a simulated video conference meeting with the self-view mode on and off at different times. In addition, an EEG-based fatigue monitor will be proposed to demonstrate the level of human mental fatigue. The experimental insights will provide direct biological evidence of the impact of video conferencing features on the user experience and these will be of benefit to inform the design of web conferencing platforms and improve the user experience of video conferencing.

Keywords: Video Conference · Fatigue Measurement · Self-View · EEG Analysis

1 Introduction

The Covid-19 pandemic has forced a dramatic increase in the number of video conferencing sessions for work purposes. In a post-pandemic world, video conferencing solutions will remain central as organisations continue to support hybrid work options. Some studies [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] have shown that engaging with certain video conferencing platform features can trigger fatigue, such as self-view mode. Some theoretical analysis indicated that being stared at was a significant predictor of Video Conference Fatigue (VCF) when users look at their screens leading to increased self-awareness. However, there are still no biological experiments to directly demonstrate the effect of self-view mode on VCF. Furthermore, many previous studies have simulated video conferencing scenarios through volunteers watching a series of videos on the computer, but this does not realistically simulate video conferencing in our opinion. In this study, we will use the self-view mode in Zoom to investigate the effect of the self-view on VCF in a real video interview scenario. A novel EEG-based VCF analysis framework will be presented and an EEG fatigue monitor will be demonstrated to show the level of mental fatigue which involves 40 volunteers. The experiment results can give us biological evidence to identify if turning on/off self-view mode can reduce the VCF. Furthermore, the effect of the self-view mode on VCF for males and females of different genders will be analysed. These findings can also inform the design of video conferencing platforms to limit the negative impacts on user well-being.

2 Problem Statement

EEG signals for VCF analysis are used to build on our insights by precisely determining how engagement with the video conferencing feature self-view mode affects user fatigue levels and if this differs between males and females. The option of self-view mode is supported on Zoom. One of the options in self-view is called “Show Self View” in Zoom, it allows the user to view themself. Another one is self-view mode off called “Hide Self View” in Zoom, it allows users to hide the video of themself from their own screen, even though others in the meeting can see their video. Recent research revealed that the self-view mode can affect the VCF through increased self-awareness and disrupts the automatic processes that are typical for effective communications [1, 6, 8, 9, 25]. While some research has investigated VCF using questionnaires in distance learning, there are still no biological experiments investigating the effect of self-view mode on mental fatigue in a real video conferencing scenario. Therefore, in this study, an EEG experiment will be conducted where the volunteer's EEG will be acquired in a real online interview conversation scenario using Zoom under the self-view mode on and off.

3 Related Work

3.1 Video Conference Fatigue

Due to the massive global use of video conferencing tools for simultaneous remote communication over the past two years, more and more people are experiencing symptoms of mental and physical fatigue. VCF is defined as somatic and cognitive exhaustion that is caused by the intensive and/or inappropriate use of videoconferencing tools, frequently accompanied by related symptoms such as tiredness, worry, anxiety, burnout, discomfort, and stress, as well as other bodily symptoms such as headaches [1]. In 2020, Morris demonstrated how mental fatigue is related to VCF and what are the causes and dynamics [2]. Mainly this is caused by exhaustion with online communication. Following the pandemic enforced lockdown and social distancing, where people have been connected using an online mode of communication, this type of mental fatigue has increased. Nadler has discussed the causes of VCF, from the online mode of communication, and the effect of cognitive load on individuals [3]. Fauville et al. used a series of surveys to measure video conferencing fatigue and indicated that frequency, duration, and burstiness of Zoom meetings were associated with a higher level of fatigue [4]. In 2021, Massner presented multi-dimensional factors that lead to VCF, such as the number of video conferences scheduled a day, the size of the video conference, the relationship among participants, the type of content shared in the video conference, the level of participation (host or participant), and the amount of interaction during the video conference [5]. In 2022, Li et al. summarised that factors causing VCF include unnatural interaction with multiple faces mental fatigue detection, self-view, asynchronicity, lack of body language, lack of eye contact, cognitive load, multitasking and reduced mobility [6]. In a study involving 33 volunteers the associations between video conference fatigue, burnout, depression and personality trait neuroticism were investigated and the study indicated that these four constructs were robustly positively associated with each other [7]. Theoretical analysis indicates that if a user's own face is shown on the interface, it may result in more pronounced perceptions of cognitive exhaustion and fatigue, due to increased attentional and working memory demands [1, 8]. Differences in fatigue by gender of video conferencing participants when they look at their screen have been identified, leading to females experiencing greater Zoom fatigue than males [9]. In this work, a neurophysiological experiment will be designed by using EEG signals to detect human mental fatigue on a video conference with the on/off self-view at different times. EEG signals can directly respond to human fatigue levels and will provide biological evidence to demonstrate how the self-view model affects VCF and to verify the impact of gender on VCF.

3.2 EEG Fatigue Measurement

In general, EEG signals are closely related to mental fatigue [10]. When large numbers of nerve cell groups are synchronised, EEG signals can record changes in postsynaptic potentials for analysis and research [11]. EEG signals have been used to detect mental fatigue in humans. In the work of Acı et al. [12], some machine learning algorithms were used for mental fatigue detection. In the work of Deng et al. [11], EEG signal provides four basic fatigue indicators. During fatigue, the slow wave increases while the fast wave decreases accordingly. At the same time, the powers of δ and θ increase, while the powers of α and β decrease. In the work of Abdulhamit [13], they indicated that within NREM sleep, δ power (slow wave power) indicates the intensity of sleep. In the work of Saroj et al. [14], they proposed an algorithm for detecting different levels of fatigue and FFT was used to transform raw EEG data into the frequency domain. In the work of Jap et al. [15], they used four algorithms for fatigue detection, which were: $(\theta + \alpha) / \beta$, α / b, $(\theta + \alpha) / (\alpha + \beta)$ and θ / β, were also assessed as possible indicators for fatigue detection. In the work of Simon et al. [16], a method for extracting EEG α spindles under noisy recording conditions was presented. In the real road driving experiment, α spindle measures could reliably identify driver fatigue and clearly differentiate between fatigue and time-on-task effects. In the work of Trejo et al. [17], they indicated that Mental fatigue was associated with increased power in frontal θ and parietal α EEG rhythms. A statistical classifier can use these effects to model EEG-fatigue relationships accurately. In the work of Ashley Craig et al. [18], they showed that as an individual grows fatigued, slow wave activity such as θ and α activity increases over the entire cortex. The results showed that as a person fatigues, slow wave activity increased over the entire cortex, in θ and in α1 and 2 bands, while no significant changes were found in δ wave activity. Table. 1 summarises the research on EEG-based fatigue analysis. It can be found that the main method of analysis is using EEG spectral information, for example using the power ratio between different EEG frequency bands and other variants (e.g. α Spindle Rate). Another option is to use classification methods to train machine learning models to detect mental fatigue.

Table 1. Summary of studies for EEG-based fatigue measurement.

Research Work	Channels	Sampling Frequency	Spectral Extraction	Mental State Classification
Deng et al. [11]	64	160 Hz	FFT	(δ + θ) / (α + β) + DCSAEN
Acı et al. [12]	7	128 Hz	STFT	SVM
Abdulhamit [13]	8	150 Hz	DWT	ANN
Saroj et al. [14]	19	256 Hz	FFT	Lab View Tool
Jap et al. [15]	30	1000 Hz	FFT	(θ + α) / β, α / β, (θ + α) / (α + β), and θ / β
Simon et al. [16]	128; 64	1000 Hz; 500 Hz	STFT	α Spindle Rate
Trejo et al. [17]	32	500 Hz	DWT-8	Linear Regression Classifier
Ashley et al. [18]	32	1025 Hz	FFT	Chalder Fatigue Scale (CFS)

4 Methodology

4.1 Volunteers and Task

To achieve our research goal, 40 volunteers will be recruited for this study. Before commencing the experiments, volunteers will complete a short survey e.g., age, gender, and video conferencing experience. Volunteers conduct two real video interview sessions under self-view mode on and self-view model off and their EEG data will be collected simultaneously. To consider possible order effects, these volunteers will be divided into two groups. The first group will have the first half of their video interview in self-view mode on (20 minutes), have 10 minutes break, and then participate in the second half via self-view mode off (additional 20 minutes). The other group of students will have the first half of the video interview via self-view mode off, have a 10 minutes break, and then participate in the second half via self-view on. Based on this procedure, possible carry-over effects can be considered in statistical analyses. The gender of each group subject will be half women and half men. In order to reduce the impact of other factors on the volunteers' fatigue and to focus on the self-view mode only, the interview questions used in the experiment will all be simple interview questions that will not significantly increase the volunteers' cognitive load. Some examples of interview questions are shown in Table 2. In addition, all experiments will be carried out in a specialist soundproof room laboratory at the department of Information Systems in University of Galway. A portable, flexible, wearable EEG acquisition device will allow the volunteers to focus more on the video conference and will minimise the impact of the EEG acquisition device on the volunteers, so a 14-channel wireless EEG headset was used in this study. The position of each channel follows the International 10-20 Montage System [19], referenced to linked ears and sampled at 256 Hz. The topographic map is shown in Fig. 1 and their names are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The Volunteers will be unified using a 14-inch MacBook Pro screen.

Table 2. Some examples of interview questions.

Session No.	Questions
1	What is your favorite color? What is your favorite animal? Do you have any pets? …
2	What are your hobbies? Do you collect anything? Who is your favorite superhero? …

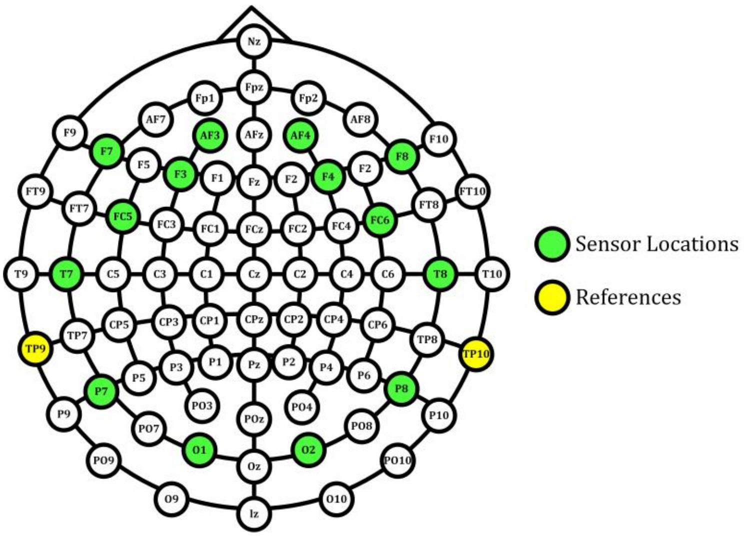

Fig. 1. The topographic map of channel position.

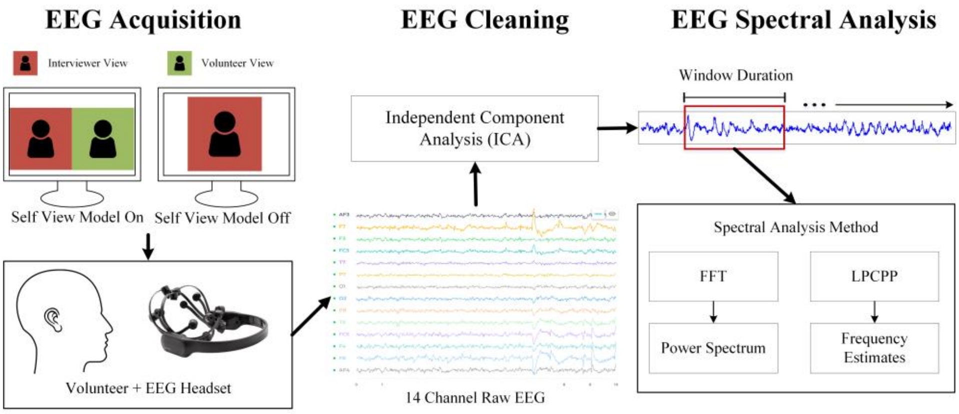

Fig. 2. Overview of the EEG-based fatigue measurement framework.

4.2 EEG-based Fatigue Measurement Framework

Many studies have shown that the power ratio between different frequency bands of EEG can be used to detect human mental fatigue. Fatigue is associated with significant changes in brainwave activity. The work of Ashley Craig et al. found that spectral activity significantly increased at the EEG θ, α1, and α2 bands when a person is fatigued [18]. In this study, a novel EEG-based fatigue monitoring framework will be provided which will use the slow wave EEG activity as the monitor to observe human mental fatigue. There is still no consensus on the definition of the different EEG frequency bands between different studies. The EEG frequency bands we use are as follows: δ (0.5–3.5 Hz), θ (4–7.5 Hz), α1 (8–10 Hz), α2 (10.5–13 Hz), and β (14–30 Hz). The overview of the framework is shown in Fig. 2 and it has three steps:

1. EEG acquisition, which corresponds to section 4.1 above.
2. EEG cleaning, where a specialist EEGLAB plug-in is used to remove artifacts from sources such as eyes and muscles using ICA and related strategies [20].
3. EEG spectral analysis, where the EEG signal from a single channel is split into 1 s window size signals and applied spectral analysis method. There are two kinds of spectral analysis methods used here:
    a. One is Fast Fourier Transform (FFT) which is a typical waveform-based spectral analysis method. It can be used to analyse the frequency content of EEG over time and give us the results of how the EEG power spectrum is distributed [11, 12, 14, 15, 16, 18].
    b. Another one is a recently proposed parameterised-based spectral analysis method called Linear Predictive Coding Pole Processing (LPCPP). This method for EEG spectral feature extraction and directly gives us numerical estimation frequency results [21, 22, 23, 24, 25].

These two typical spectral analysis methods, FFT and LPCPP, will be used to observe the EEG power spectrum and the number of changes in the EEG dominant frequency estimates respectively to see the differences in EEG spectral and therefore to observe the differences in fatigue. The details of the experimental results are in section 4.3.

4.3 Experimental Results

Two forms of spectral results from the FFT and LPCPP will be used to analyse the EEG spectral activity, the power spectrum and the dominant frequency estimates. These results were further processed to measure EEG spectral activity. One is Average Spectral Power (ASP) which is used to measure the spectral power changes results. Another one is the Probability Distribution Function (PDF) which is used to describe the probability of EEG dominant frequency estimates. The purpose of this study is to observe the human fatigue difference between the self-view model on/off. A series of spectral results at the self-view mode on/off using ASP and PDF will be demonstrated here, such as:

1. The differences between different genders (i.e. male and female)
2. The differences between different EEG channel locations.
3. The differences between the different EEG bands.

5 Current Progress and Future Direction

Currently, we have recruited 40 volunteers to take part in the study, of which half are male and half are female, all of them from the University of Galway. The data acquisition is expected to be completed by the end of March. We plan to spend 2-3 months cleaning and analysing the EEG data to identify if turning on/off self-view mode is more likely to produce VCF. In this study, an EEG-based framework for VCF analysis is presented. The design of the experiment focuses on the self-view mode, a typical feature of VCF in video conferencing. The analysis of EEG signals can help us to build on our insights by precisely determining how engagement with self-view mode in video conference platforms affects user fatigue levels. The results of these analyses will be used to inform the design of video conferencing platforms and improve the user experience of video conferencing. An output of the experiment will be the creation of a new EEG dataset which involves 40 volunteers. In the future, more kinds of biological signals (e.g. ECG, EMG, EOG) could be considered to help provide more insights for the optimisation of video conferencing platforms.

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