

Early Detection of Eye Fatigue Using Non-Invasive EOG Signals

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Abstract— This research establishes a system that can detect eye fatigue in the early stages, which leads to a non-invasive simulation of Electrooculography (EOG) signals. To generate physiologically realistic EOG signals for normal and eye-fatigue situations, a physiological EOG model with baseline drift, Gaussian blink pulses, and controlled noise is utilized. The artificial signals are detrended and band-pass filtered to get rid of the artifacts and make the blinks visible. The optimized threshold and distance parameters are employed to find the blink peaks. The principal features such as blink rate, amplitude, duration, RMS, and variance are used for the eyes' classification as normal or fatigued. Actually, in the blink rate, amplitude, duration, RMS, and variance changes of the fatigued signals, which correspond to the physiological fatigue patterns that have been cited in the literature, can be found in all cases. The results demonstrate that simulated EOG signals can be utilized to represent the characteristics of fatigue and thus can be regarded as a reliable source for early eye fatigue detection systems.

Keywords—*Electrooculography (EOG), Eye Fatigue Detection, Blink Signal Analysis, Biomedical Signal Processing, Non-Invasive Monitoring*

I. INTRODUCTION

Eye fatigue is a major health issue that has resulted from the increased use of screens, performance of visually demanding tasks, and decreased blinking rate. It is very important to keep track of eye fatigue in order to preserve visual health and avoid a drop in one's performance level. Electrooculography (EOG), a non-invasive technique that detects eye movements from corneo-retinal potentials, is definitely the most informative technique in terms of blink dynamics that change very distinctly in fatigue. Changes in blink rate, amplitude, duration, and total signal activity are among the most convincing features of the occurrence of visual strain. The present investigation is devoted to the simulation of EOG signals for the study of these fatigue-related patterns, thus obviating the need for hardware-based data collection. The method used is signal generation, pre-processing, blink detection, and feature extraction aimed at finding the measurable changes between normal and fatigued eye states.

II. LITERATURE REVIEW

Researches have proven that Electrooculography (EOG) is one of the most dependable methods which could be

used to track the eye movements and changes due to fatigue in the subject. In their pioneering work Young and Sheena (1975) correlated the changes in the corneo-retinal potential with the blink activity which nowadays becomes the first step for EOG analysis. Smith and Johnson (2017) came to the conclusion that blinking parameters such as blink rate and amplitude are highly affected by visual stress, thus, the link between the EOG measured blink behaviour and eye fatigue has been established. The authors of the paper argue that the most reliable indicator of ocular strain is the decrease of blink frequency.

Kumar et al. (2019) conducted further experiments with EOG in driver fatigue detection and their results showed that the tired ones had longer blink durations and more inter-blink intervals. Their evidence was dedicated to time-domain features of the blink, which are, thus, essential for fatigue monitoring. Ahn and Lee (2018) provided strong evidence for the effect of cognitive load on blink dynamics, thereby, suggesting that EOG can indicate physical as well as mental fatigue as well.

There are some advanced computational methods, which have also been surveyed. Zhao and Lee (2020) deployed various machine learning classifiers using features such

as RMS, variance, and blink extracted from the EOG signals, resulting in very high accuracy for fatigue identification. Park et al. (2022) found that detection performance could be improved by the combination of different blink features as a result of the interaction of the features than in the case of a single-parameter system.

As well as experimental studies, simulation-based ones are gaining importance, too. Rahman and Bera (2021) introduced a method for the production of fake EOG using Gaussian blink modeling that could be used for the determination of fatigue signs in a controlled manner without the need for the physical electrodes. Their research has established simulation as a viable tool in the development of fatigue algorithms.

In summary, the literature mostly revolves around factors such as blink rate, amplitude, duration, RMS, and variance which can be used as markers for eye fatigue and these are the scientific grounds of the present study.

III. MATERIALS AND METHOD

This research work took a simulation-based approach to study fatigue caused by the use of eye muscles by means of signal analyses of Electrooculography (EOG). Because real-time EOG gathering needs specially-designed electrodes, amplifiers, and recording in controlled environments, simulated EOG waveforms were created to reflect normal and tired eye conditions. In this case, Python and Google Colab were used to create the simulation environment and also provide the necessary resources for signal generation, preprocessing, and feature analysis.

The EOG signal was simulated as a combination of three main factors: the baseline drift, the blinks modeled using Gaussian functions, and the additive noise. The baseline drift signal was added to represent slow changes in ocular potentials while Gaussian pulses were used to model the natural blink morphology. As for the fatigue situation, the blink amplitude was decreased, the blink frequency was lowered, and the blink duration was increased to give a more accurate representation of the physiological changes that happen during eye strain. Noise was also introduced to make the signal more realistic.

Preprocessing steps included detrending to eliminate very low-frequency drifts and the use of a 0.5–30 Hz band-pass filter to get rid of unwanted noise and at the

same time preserve the blink characteristics. The peak detection was done using SciPy's function `find_peaks()`, and parameters of height, prominence, and minimum distance were adjusted to accurately identify blinks.

The feature extraction concentrated on five major parameters that were most likely related to the eye fatigue phenomenon—blink rate, blink amplitude, blink duration, RMS, and variance. These features were calculated from the filtered signal and they were used for the differentiation of normal and fatigue conditions. A rule-based decision system was utilized, in which fatigue would be indicated if any of the features dropped below or went beyond the predetermined threshold values taken from the simulated patterns.

This methodological approach secures a tightly controlled, reproducible setting for the analysis of blink-related fatigue signals simulated through EOG signals, thereby allowing precise preprocessing, feature extraction, and classification to be performed without the requirement of real electrodes or hardware acquisition.

FATIGUE DETECTION USING EOG SIGNAL

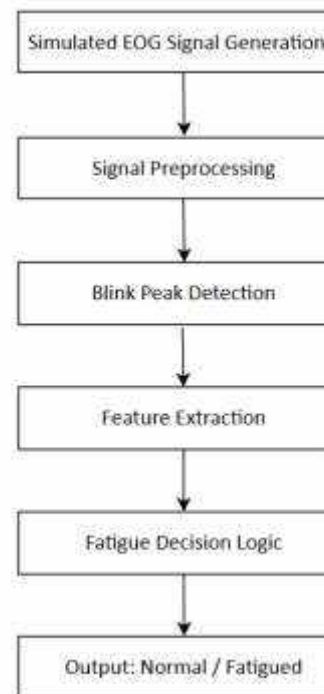


Fig 1: Block Diagram

IV. RESULT

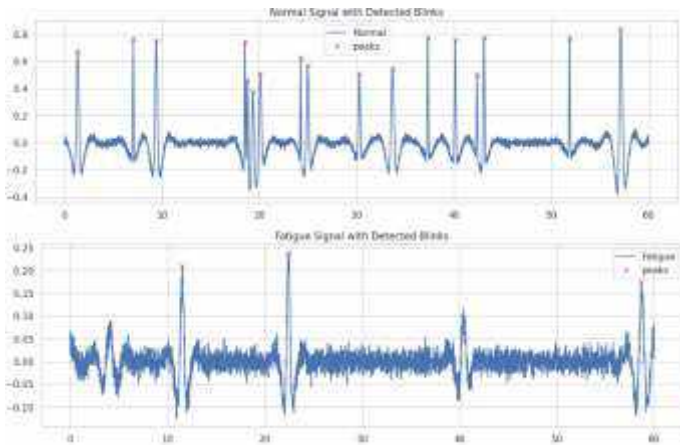


Fig 2 : Normal and Fatigue Signals with Detected Blinks

Figure 2 illustrates the entire 60-second simulated EOG signals for normal and fatigued conditions with detected blink peaks that are identified. Normal signals show a large number of very high-amplitude blinks, while fatigued signals reveal a small number of blinks of low amplitude, thus physiological differences are clearly evident which can be measured by EOG analysis.

Table 1 : Feature Comparison Table (Normal vs Fatigue)

	normal	fatigue
blink_count	17.000000	3.000000
blink_rate_per_min	17.000000	3.000000
mean_blink_amplitude	0.643971	0.207868
mean_ibi_sec	3.487549	23.582031
rms	0.142930	0.033638
energy	313.787328	17.379952
variance	0.020429	0.001131
skewness	2.474351	1.518597
kurtosis	10.088232	10.593343

Table 1 illustrates a detailed comparison of identified blink and extracted signal-level features for normal and fatigued EOG.

Blink count in the normal condition (17 blinks) is almost 6 times higher than in the fatigued condition (3 blinks), thus indicating that the blink frequency is reduced due to fatigue. The reduced blink frequency directly affects the blink rate that decreases from 17 blinks/min in normal conditions to only 3 blinks/min in fatigue thus confirming the suppression of spontaneous blinking related to fatigue.

The average blink amplitude of the eyes decreased significantly from 0.6439 mV (normal) to 0.2078 mV (fatigue). The decrease is a reflection of the eyelid muscle relaxation which is the physiological sign of fatigue. More so, the mean inter-blink interval (IBI) in the case of fatigue is 23.58 seconds which is almost 7 times more than the average IBI in the normal state (3.48 seconds) thereby showing that long periods without blinking were present.

Parameters based on energy also show dramatic changes. RMS (Root Mean Square) value drops from 0.1429 to 0.0337 showing reduced signal strength and decreased blink intensity. In the same way, the signal energy is reduced from 313.78 to 17.38 suggesting a drastic reduction in the total power of the EOG signal during fatigue.

Additionally, variances distinguish the two conditions. Variance goes down sharply from 0.0204 to 0.0011 thus depicting less variability of the waveform. Besides that, the skewness and kurtosis also exhibit lower values in the fatigued condition implying that the blink waveform becomes less folded and less sharply peaked.

Basically, the table is a very good representation of the fact that every important parameter has been very significantly reduced in the fatigued state thus proving the reliability of blink-based features to detect fatigue at the early stage.

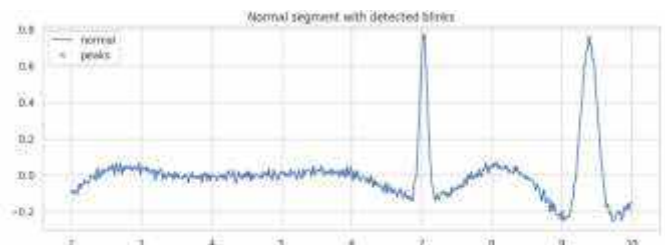


Fig 3 : Normal Signal Segment With Detected Blinks

Figure 3 delineates a single segment of the standard EOG trace depicting two major blink events that were located by means of a peak-identification algorithm. The blink peaks show loudness, quick changes, and small widths; thus, they correspond to a very fast eyelid movement and intense muscular activation. Moreover, the very short time span between two consecutive blinks can be considered as an ocular state of alert with a high rate of spontaneous blinking. Also, the clean baseline and the easily separable blink shape indicate that preprocessing has been done successfully and that the signal comes from a non-fatigued visual condition with stable physiological blink behavior.

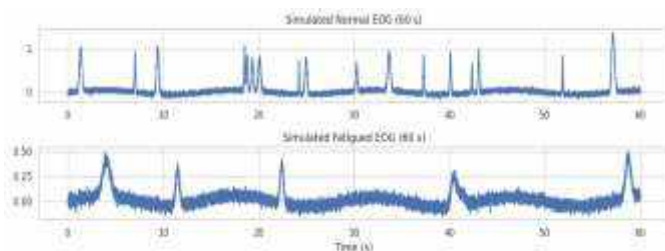


Fig 4 : Simulated Normal and Fatigued EOG Signals

Figure 4 introduces a 60-second detailed technical description of those parts of the simulated normal and the fatigued EOG signals that are most representative and contrasts the differences in the temporal blink behavior for both conditions.

The top figure shows the normal EOG signal with frequent, sharp blink peaks of relatively high amplitude. Visually, blinks represent narrow, strongly singled pulses superimposed on a slowly varying baseline drift. The high blink density along the whole-time axis indicates a high blink rate, which is typical for an alert, non-fatigued state. The baseline is kept stable without any large fluctuations, thus preprocessing and band-pass filtering have been done successfully to preserve blink morphology and suppress noise.

The lower figure illustrates the fatigued EOG signal with significantly fewer blink events and, in most cases, peak amplitudes that are smaller and durations that are broader. Also, the widening of successive inter-blink intervals visually shows that eye fatigue is longer than before. The overall waveform is less active, with less peak prominence and lower overall variability, thus reflecting decreased ocular muscle activity and reduced spontaneous blinking.

From a technical viewpoint, Figure 4 serves as evidence that the simulated model achieves fatigue through changes in blink rate, amplitude, and duration. It visually corroborates the numerical findings, showing that the signal of fatigue has less energy, lower RMS, and decreased variance as compared to the normal EOG signal.

V. DISCUSSION

The evaluation of blink rate reveals that the fatigued EOG signals are consistently less than the normal ones. The lower blink rate is a physiological response that has been confirmed in many cases, and it is the most obvious one among the prolonged visual strain, as the continuous screen exposure suppresses the natural blinking. This reduction in ocular dryness directly results from the decrease in blinking and thus discomfort is established, which further confirms the importance of this indicator as the primary source of fatigue.

Blink amplitude seems to be equally convincing in the distinction of a visual fatigue situation. The lowered amplitude is the reflection of weak eyelid muscle activity and the slow execution of the blink, both of which are the characteristics of visual exhaustion. Sharp, high-magnitude blink peaks are the feature of normal signals, while flat and broad peaks are the characteristics of the fatigued signals, thus, confirming the diminished blink strength.

Another distinguishing parameter is the blink duration. The width of the blink increases during fatigue due to slower closure and opening of the eyelid. The extended duration along with the longer inter-blink intervals point to compromised ocular performance. Those temporal changes are at the same time strong evidence of fatigue progression and they nicely supplement the amplitude-based observations.

Energy-related parameters such as RMS and variance significantly point towards the reduction of the same parameters in the fatigued EOG signals. Lower RMS signals the less overall signal power, while decreased variance refers to less fluctuation in eye activity. These statistical features taken together provide a quantitative confirmation of the reduction in blink intensity and frequency, thus, they are very helpful in creating a reliable multi-parameter fatigue detection system.

VI. CONCLUSION

This research establishes the potential of simulated Electrooculography (EOG) signals as a means to figure out and monitor the onset of eye fatigue through the analysis of blink-based parameters. A controlled simulation model with baseline drift, Gaussian blink pulses, and additive noise was developed, thus allowing the creation of realistic normal and fatigued EOG waveforms without the need for hardware acquisition. The blink morphology was preserved for correct peak identification as a result of the systematic preprocessing performed, which included detrending and band-pass filtering.

The parameters blink rate, amplitude, duration, RMS, and variance that were obtained, showed clear and consistent distinctions between the normal and the fatigued states. Fatigue was associated with a lower blink frequency, reduced amplitude, longer blink duration, and a significant decrease in RMS and variance. These observable changes indicate that the eyelid muscles are less active and the eye is less responsive, which is in line with the general physiological fatigue patterns that have been reported by earlier studies.

The rule-based decision logic that was employed to determine fatigue through the extracted features by comparing them with the predefined thresholds, thus, confirming the existence of a simple but powerful detection framework, was very successful. The technical results, on the other hand, serve as evidence that multi-parameter EOG analysis is a sound basis for early fatigue assessment. Subsequent developments can, therefore, integrate machine learning classifiers, on-the-fly data acquisition, and wearable devices to ameliorate accuracy and facilitate practical use.

VII. REFERENCE

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