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Drowsiness Detection via Blink Analysis Using EOG Signals and MATLAB Visualization

***Abstract*—Drowsiness while driving represents a critical road safety issue and is one of the leading causes of motor vehicle accidents. These incidents can be prevented by monitoring physiological indicators, with ocular activity particularly blink frequency and amplitude being one of the most informative variables. In this context, the primary objective of this research was to design a basic system for the acquisition and processing of electrooculographic (EOG) signals, aimed at detecting drowsiness through the analysis of eye movement patterns. An experimental methodology was employed, which included a literature review of previous studies on EOG and fatigue, the development of a prototype using an Arduino UNO microcontroller and a signal amplification module, as well as the implementation of a graphical interface in MATLAB for real-time signal visualization and analysis. The system applied band-pass digital filtering, signal normalization, and a blink-counting logic within 60-second time windows.**

The most significant result was the system's ability to detect sustained reductions in ocular activity in real time and to automatically trigger alerts upon identifying signs of fatigue achieved without the need for complex algorithms or prior training. It is concluded that the prototype successfully meets the stated objective, demonstrating the feasibility of implementing an accessible tool for alertness monitoring based on EOG signal analysis. This development provides a foundation for future scalable applications in real world environments.

***Index Terms*—Blink analysis, Drowsiness detection, Electrooculography, Eye movement tracking, Real-time monitoring**

I. Introduction

In 2024, the National Highway Traffic Safety Administration of the United States of America estimated that approximately 100,000 crashes each year are primarily caused by drowsy driving, resulting in more than 71,000 injuries. This highlights the importance of having a means to detect a driver's drowsiness before an accident occurs.

The Electrooculogram (EOG) is a useful biological signal for monitoring eye movements through surface electrodes, recording the electric potential between the cornea and the retina. This signal allows for the identification of horizontal and vertical displacements, including saccadic movements and fixations. Eye activity has been closely linked to drowsiness, as fatigue alters the frequency, amplitude, and speed of these movements. Therefore, the EOG requires appropriate preprocessing to eliminate artifacts and detect key events such as blinks and slow eye movements (SEMs).

EOG is based on the bioelectrical activity generated by the extraocular muscles, taking advantage of the electric potential that exists between the cornea (positive) and the retina (negative). When the eyes move, this electrical field changes, producing a signal that can be recorded using surface electrodes strategically placed on the skin. The resulting signal has amplitudes ranging from 0.05 to 3 mV, depending on the type and direction of the eye movement [1].

This investigation presents a review from previous research about eye activity and its applications for detecting drowsiness. Furthermore, it proposes the design of an initial prototype of a basic EOG system that enables the real-time analysis of eye movements, with the aim of identifying and presenting possible relevant patterns for the development of technologies focused on monitoring physiological states, especially those related to the detection of drowsiness.

A. *State of the Art*

1) Types of Eye Movements: The most relevant eye movements in EOG analysis include saccades, smooth pursuit, fixations, and blinks. Saccades are rapid movements that allow the gaze to jump between visual targets; smooth pursuit keeps moving objects centered in the visual field; fixations stabilize the gaze to gather information; and blinks [2]. These movements are useful for assessing attention, cognitive state, and fatigue. Studies such as those by Behrens et al. [3] and Santini et al. [4] have proposed algorithms that improve the detection and classification of these movements, even using low-cost hardware, which broadens their applicability in continuous monitoring contexts.

2) Relationship between drowsiness and eye activity: Hypovigilance is a phenomenon in which a person's alertness and concentration decrease over time, affecting their performance in tasks that require focused attention. Electrooculographic (EOG) signals offer high temporal resolution and various features that make them useful for detecting drowsiness. They allow for clear distinction between horizontal and vertical eye movements, with blinks being exclusive to vertical eyelid movements. During fatigue, eye movements decrease while blink frequency increases. Additionally, EOG captures two patterns: rapid eye movements, which occur when the person is awake, and slow eye movements, which appear during drowsiness. Increased blink duration and the presence of slow eye movements are clear indicators of drowsiness [5].

The EOG signal measures eye movements and blinks, which change significantly with drowsiness. Under normal conditions, a person blinks between 12 and 15 times per minute, with an average blink duration of 202 milliseconds. When a person is drowsy, blink frequency decreases, and blink duration increases to an average of 258 milliseconds. Similarly, the amount of time the eyes remain closed becomes longer [6].

3) Extraction of Relevant EOG Features: Feature extraction plays a key role in the analysis of electrooculographic (EOG) signals, as it enables the identification of relevant patterns associated with ocular movements, including saccades, fixations, and blinks—events that serve as indicators of alertness or drowsiness. One of the most widely used techniques for this purpose is the Fast Fourier Transform (FFT), which allows the identification of dominant frequency components and temporal patterns within the EOG signal [7].

4) Current Applications of EOG: Electrooculography (EOG) is widely used in both clinical diagnostics and technological applications. In medical contexts, the Arden ratio is a key indicator of retinal pigment epithelium function. This metric evaluates the relationship between the potentials recorded under light exposure (light peak, LP) and in darkness (dark trough, DT), with values below 1.5 suggesting retinal dysfunction [8].

In the area of assistive technology, EOG signals are used to control devices such as wheelchairs, virtual keyboards, and home automation systems, contributing to greater autonomy for individuals with motor impairments [9]. EOG has also been applied in human–machine interfaces, enabling control of cursors or interaction with video games through ocular movement patterns [9].

A particularly relevant application is driver fatigue detection, where EOG is used to analyze slow eye movements (SEMs), blink frequency, and signal amplitude fluctuations [10]. In this context, systems using frontal electrode configurations in Fig. 1 have been developed to capture both horizontal and vertical EOG components (HEO and VEO), enhancing user comfort [11].

In recent studies, supervised classification algorithms such as Support Vector Machines (SVM) and Generalized Extreme Learning Machines (GELM) have been applied to short EOG segments to identify SEMs and improve real-time system responsiveness [12]. Moreover, EOG has been integrated into brain–computer interface (BCI) systems, often in combination with EMG and EEG signals, to increase the range of available control commands, particularly for individuals with severe motor disabilities [13].

5) Comparison between EOG, EEG, and Other Monitoring Techniques: Shahbakhti et al. [19] proposed a hybrid monitoring model for driver fatigue detection, combining EEG signals and blink parameters obtained through EOG. Their research focused on a single prefrontal EEG channel, making the system more comfortable and less invasive. The comparison between EEG and EOG in this context is relevant: EEG provides information on brain electrical activity, useful for identifying transitions to low-alertness states by analyzing alpha and theta bands. Meanwhile, EOG detects ocular events such as prolonged blinks, reduced blink frequency, or slower eye movements, all of which are directly linked to drowsiness. Integrating both systems offers a broader and more precise analysis of fatigue and sleepiness.

Similarly, Wang et al. [17] presented an intelligent fatigue recognition system during driving, based on multisensory integration of EEG and ECG signals combined with computer vision techniques. Their model used non invasive sensors to record EEG signals focused on theta and alpha waves associated with low alertness and ECG signals to measure heart rate variability, another fatigue indicator. This multimodal approach allows the system to correlate internal physiological signals with external signs of drowsiness, achieving a more accurate and sensitive assessment than would be possible using a single biological signal alone.

II. Methodology

This research had a qualitative, applied, and experimental approach, aimed at developing a basic EOG prototype for drowsiness detection. A system was designed to acquire, process, and visualize signals in real time, considering parameters such as blink frequency, decreased eye activity, and variation in fixation duration. The methodology was structured in stages, supported by scientific literature, which allowed for defining key technical elements such as filter types, electrode placement, and reference values for signal amplitude.

The variables were divided into independent and dependent. The system design, including the number and placement of electrodes as well as software processing, constituted the independent variable. The dependent variables were related to the captured eye activity, such as blink frequency, prolonged fixations, and absence of peaks in the signal. These signals were recorded using three surface electrodes connected to an EMG module, with digital processing based on a FIR (a Finite Impulse Response) bandpass filter from 0.5 to 10 Hz. Finally, a graphical user interface was integrated to visualize the signal and trigger alerts in case of sustained low eye activity.

A. Acquisition System Design

For EOG signal acquisition, three surface electrodes were used, connected to an EMG module that amplified the signals before sending them to an Arduino microcontroller, as seen in Fig 1. This microcontroller was selected because it has proven to be very useful for acquiring and transmitting electrooculographic (EOG) signals in real time, capturing signal amplitudes ranging from 0.05 mV to 3 mV [15]. It enabled a low-power implementation, ideal for continuous monitoring systems such as drowsiness detection. The microcontroller was responsible for receiving the analog signal from the EMG amplification module because, with proper signal filtering and adaptation settings, it detects the signal better compared to a cardiac sensor, which may filter out relevant noise in the ocular signal [16].

Furthermore, it has been demonstrated that these amplifier modules are ideal as biosensors [17]. Regarding electrode placement, they were positioned along the vertical ocular axis, as it has been proven [11] that this arrangement measures the potential difference during up-and-down eye movements and blinks. The main components used for the development of the system were the following:

- Surface electrodes placed around the eye.

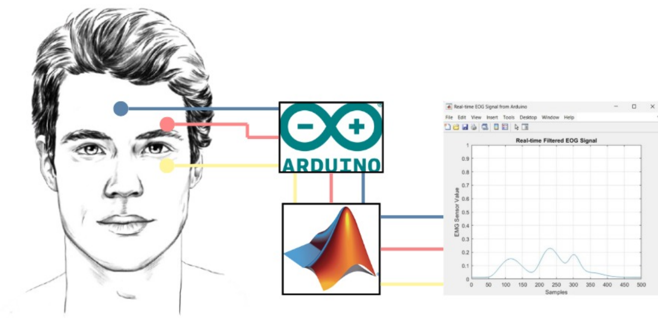

Fig. 1. Electrode configuration

- EMG sensor responsible for amplifying the captured signals.
- Arduino UNO microprocessor, which digitizes and processes the signal using digital filters.
- Graphical visualization software.
- Alarm to emit auditory alerts.
- Wires for circuit assembly.

B. Signal Processing

The acquired signal was digitized and processed using digital filters available in the Signal Processing Toolbox in MATLAB. This has proven to be a valuable tool for physiological signal processing, and in this case, a bandpass filter (0.1–10 Hz) was applied to eliminate muscular, electrical, and baseline artifacts [18]. The system analyzes the signal in moving 60-second windows as a primary indicator of drowsiness [7].

C. Real-Time Visualization

The system includes a graphical user interface that displays the EOG signal as an amplitude versus time graph. In addition to the waveform, additional information such as the number of detected blinks and their frequency is shown. If prolonged eye inactivity is detected, a visual alert is triggered on the screen along with an auditory signal emitted by an alarm.

D. Drowsiness Detection

At the start of the program, a time window is activated to
12 capture signal peaks related to eye movement. The signal is acquired in real time, filtered, and normalized to eliminate noise, then displayed graphically. For 60 seconds, the system counts peaks that exceed an adaptive threshold, incrementing the counter as appropriate and classifying the type of move-
13 ment depending on the peak duration: if it is greater than 0.16, it is classified as SEM; otherwise, it is classified as REM. At the end of the time window, if the counter is 12 or more, no drowsiness is detected; if less, a sound alarm is triggered. The process automatically restarts for a new cycle Fig. 2.

E. Prototype Validation

Validation was conducted through controlled testing with five voluntary users (three women and two men) between the ages of 21 and 22. Periods of low eye activity and

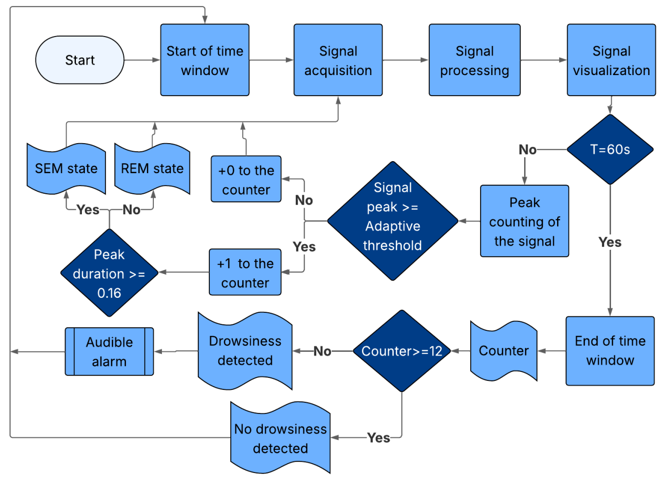

Fig. 2. Flow diagram of the Matlab code

blink frequency were evaluated in real time, verifying whether the system correctly generated alerts when detecting patterns compatible with drowsiness. Additionally, signal stability was reviewed, meaning the consistency and quality of the signal obtained during measurement. The system's sensitivity to actual eye movements and the effectiveness of the applied filters in mitigating interference and artifacts were also evaluated.

The testing protocol consisted of three stages. In the first, users performed normal eye movements, including spontaneous and voluntary blinks. In the second, participants were instructed to maintain a fixed gaze for 60 seconds to evaluate baseline noise and the generation of false positives. In the third, moments of drowsiness were considered, whether due to boredom or reading something uninteresting, during several 60 second analysis windows to assess their SEM state.

The system classified each event based on previously defined amplitude and duration thresholds, and the resulting predictions were compared to the labeled dataset to assess accuracy. Events classified as REM corresponded to sharp peaks lasting 0.2 seconds or less in Fig. 3, while SEM were identified as smoother, longer lasting waves in Fig. 4 [5]. This test enabled the construction of a confusion matrix, from which metrics such as precision, recall, and overall accuracy were derived, allowing for an analysis of the program's performance under real conditions without the need for machine learning models. This methodology provides data to evaluate the project's feasibility for integration in real-time environments such as drowsiness detection while driving or during prolonged surveillance tasks.

III. Results and Discussion

Real-time visualization was achieved using a MATLAB interface, which also classified events based on waveform amplitude and duration.

Drowsiness detection was performed through a peak counting algorithm applied over 60-second windows. A threshold of 12 blinks per minute was used as the reference value. When

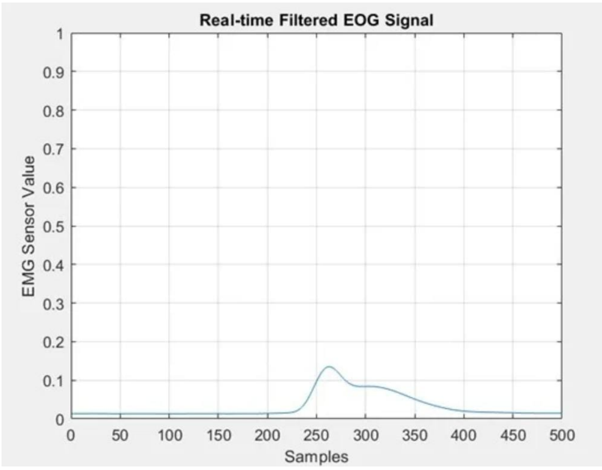

Fig. 3. REM state waveform

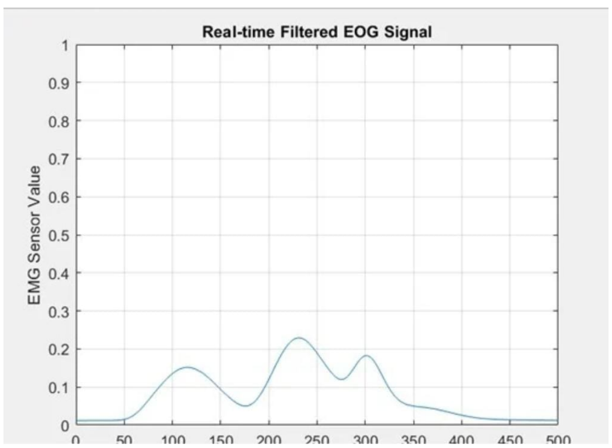

Fig. 4. SEM state waveform

the blink rate dropped below this limit, the system generated both visual and auditory alerts.

30 The initial tests showed three distinguishable patterns: normal activity (14–18 blinks/min), early drowsiness (9–12 blinks/min), and low alertness (6 blinks/min). The prototype correctly classified these states with an estimated accuracy of 80%.

During testing, it was observed that underlying ocular conditions and environmental variability could influence the recorded EOG patterns, even in the absence of drowsiness. These factors introduced inter-user variability in signal frequency and amplitude, reinforcing the importance of individualized thresholds and controlled testing environments.

Future improvements should include advanced signal processing techniques and a larger, more diverse participant group to refine detection accuracy. Beyond drowsiness monitoring, EOG analysis holds potential for studying how clinical and environmental conditions affect ocular dynamics, supporting the integration of such systems into broader real-time alert
29 applications. The confusion matrix presented in Fig. 5 shows the performance of the program targeted to classification

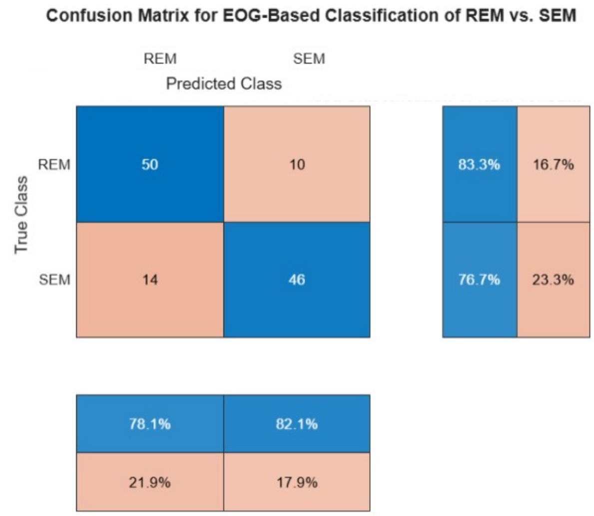

Fig. 5. Confusion Matriz for EOG-Based Classification of REM and SEM

system between REM and SEM stages. The system correctly classified 50 out of 60 REM events and 46 out of 60 SEM events, yielding an overall accuracy of 80%. The sensitivity (true positive rate) was 83.3% for REM and 76.7% for SEM, while the precision (positive predictive value) was 78.1% for REM and 82.1% for SEM. The matrix also indicates that 21.9% of the samples predicted as REM were actually SEM, and 17.9% of those predicted as SEM were in fact REM. These results confirm that the signal processing-based approach without using of artificial intelligence, it achieves a robust performance in detecting eye movement stages relevant to somnolence, supporting its potential for real time, low cost monitoring applications.

IV. Conclusions

This research led to the design and implementation of a basic prototype for EOG signal acquisition and processing, focusing on the detection of drowsiness through ocular pattern monitoring. Despite its low amplitude and susceptibility to noise, the EOG signal was found to carry relevant information, particularly regarding blink frequency and the presence of slow eye movements.

A pattern classification method was designed using an adaptive threshold and blink-counting logic within defined time windows. This approach enabled the system to detect reductions in blink frequency as potential signs of drowsiness, activating visual or auditory alerts accordingly.

These findings reinforce the value of EOG as a noninvasive tool for monitoring physiological variables, with potential applications in contexts such as prolonged driving, visual fatigue, or alertness assessment. Future research could incorporate machine learning algorithms and more advanced acquisition hardware to improve adaptability among users and improve detection accuracy.

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