

A Real-Time Multimodal Human Fatigue Monitoring System Using GSR and Vision-Based Facial Analysis

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Abstract- Human fatigue and drowsiness can reduce attention and task performance, motivating the development of real-time monitoring systems that combine behavioral and physiological indicators. This paper presents a low-cost prototype that combines galvanic skin response (GSR) sensing with vision-based facial analysis. An R-1085 GSR sensor is interfaced to an ESP32 for analog signal acquisition and USB serial transmission. A conventional laptop camera provides facial images, while Python, OpenCV and MediaPipe facial landmarks are used to estimate eye aspect ratio (EAR) and identify prolonged eye closure. LabVIEW 2022 is proposed as the supervisory monitoring layer for visualization and alert presentation, with a buzzer available for warning output. Initial GSR experiments using 35 finger-contact samples produced values from 2242 to 2270 (mean 2262.4; standard deviation 4.75), whereas 37 no-contact samples ranged from 2366 to 2490 (mean 2400.38; standard deviation 23.81). The camera prototype produced EAR values of 0.39 for an open-eye frame and 0.19 for a closed-eye frame. These preliminary results demonstrate operation of the individual sensing components. The prototype is intended for research and educational evaluation; the measured thresholds are not clinically validated fatigue criteria.

Keywords: human fatigue monitoring; galvanic skin response; GSR; ESP32; facial landmarks; eye aspect ratio; MediaPipe; sensor fusion.

I. INTRODUCTION

Fatigue and drowsiness are important human-state conditions because reductions in vigilance and sustained attention can affect performance in transportation, industrial work and other safety-critical activities. Monitoring approaches generally use behavioral, physiological, vehicle-based or multimodal information. Reviews of the field show that physiological measures such as galvanic skin response (GSR), together with eye-related measures, have been investigated for fatigue and drowsiness monitoring, but validation and generalization remain significant challenges [1-4].

Vision-based monitoring is attractive because a conventional camera can provide non-contact information about the eyes and face. Eye aspect ratio (EAR) is a compact geometric measure of eye opening derived from facial landmarks and has been used for real-time blink detection [5]. PERCLOS, which measures the proportion of time that the eyes are substantially closed, is also an established drowsiness-

related measure, although recent evidence indicates that no single visual index is sufficient for all real-world conditions [6].

Physiological measurements can provide complementary information, but they are affected by subject-specific factors and measurement conditions. A systematic review of physiological drowsiness detection found substantial variation across studies and emphasized the need for validation on new samples [2]. These observations motivate a prototype that does not rely on a single indicator. The present work therefore combines a low-cost GSR channel with camera-based facial analysis, with ESP32 used for data acquisition and a computer used for higher-level processing and visualization. The original project concept considered thermal infrared facial sensing; however, the implemented prototype described in this paper uses a normal laptop RGB camera. Consequently, the present system makes no temperature measurement and does not claim thermal-imaging capability. The objective is to demonstrate a practical multimodal fatigue-monitoring architecture and establish experimentally measured baseline behavior of its sensing components.

II. RELATED WORK

Fatigue-monitoring research spans wearable physiological sensing, computer vision and multimodal systems. Adão Martins et al. reviewed wearable fatigue-monitoring studies and reported the use of GSR, ECG, EEG, EMG, eye movement and other physiological or behavioral signals, while also identifying limitations related to data quality, study duration and generalizability [1]. Saleem et al. similarly reviewed physiological-signal-based driver drowsiness systems and highlighted differences in sensing modalities, experimental settings and validation procedures [2]. Albadawi et al. categorized driver drowsiness systems into biological, image-based, vehicle-based and hybrid approaches and emphasized practical and reliability challenges [3].

For visual monitoring, Soukupová and Čech proposed a real-time eye-blink method based on facial landmarks and EAR, showing that landmark geometry can provide a compact measure of eye opening from a standard camera [5]. MediaPipe provides a general perception framework for real-time facial landmark processing and has been used to build cross-platform perception applications [7]. PERCLOS-based methods provide another established approach to estimating drowsiness from eye closure, but a recent review concluded that PERCLOS should be combined with other behavioral or physiological indicators for broader robustness [6]. Recent multimodal reviews continue to identify sensor fusion as an important direction, while also noting that many published systems are evaluated on small or controlled datasets and have limited real-world validation [4]. The contribution of this work is therefore not a claim of a new clinically validated fatigue classifier, but a reproducible low-cost prototype that integrates GSR acquisition, facial landmark analysis and supervisory monitoring.

III. PROPOSED SYSTEM

The proposed system consists of two sensing paths. The first path acquires GSR through an R-1085 skin-response module connected to an ESP32 analog input. The second path uses the built-in RGB camera of a laptop to acquire facial images. The ESP32 transmits GSR samples over USB serial, while Python processes camera frames using OpenCV and MediaPipe. The two

information streams are brought together at the software level to support a prototype fatigue-warning decision. LabVIEW 2022 serves as the planned monitoring interface for displaying the GSR waveform, numerical values, eye state and warning status.

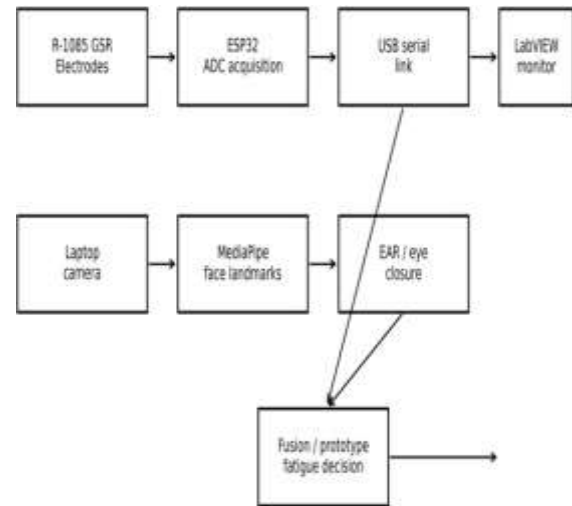


Fig. 1. Proposed architecture of the multimodal human fatigue monitoring prototype.

1. Hardware And Data Acquisition

The R-1085 module provides an analog output associated with skin contact and is connected to the ESP32 using a 3.3 V supply, common ground and an analog signal connection. In the implemented test configuration, the signal was read using GPIO34. The ESP32 platform provides analog-to-digital conversion and serial communication capabilities suitable for low-cost sensor acquisition [8]. The sensor electrodes are connected only to the GSR module, and the module output is sampled by the ESP32.

A conventional laptop camera is used for facial sensing. This choice reduces hardware complexity and cost compared with a thermal infrared camera, but it also means that the system is sensitive to lighting, pose, occlusion and camera placement. The system therefore treats the camera channel as a vision-based behavioral indicator rather than a temperature sensor.

2. Vision-Based Eye Analysis

Each camera frame is converted to the required image representation and passed to the MediaPipe Face Landmarker. Facial landmark coordinates are then used

to calculate EAR for the left and right eyes. For an eye represented by six landmark points, EAR is calculated as:

$$EAR = (\|p_2 - p_6\| + \|p_3 - p_5\|) / (2\|p_1 - p_4\|) \quad (1)$$

where the numerator contains the two vertical eye-opening distances and the denominator represents the horizontal eye width. A lower EAR corresponds to a more closed eye. In the prototype, an EAR below is treated as a closed-eye condition, and continuous closure for approximately 2 s generates a prototype warning. These values are engineering thresholds selected for the demonstration and are not validated fatigue thresholds.

The visual implementation was tested using a standard laptop camera. In one captured frame with the eyes open, the displayed EAR was 0.39. In another captured frame with the eyes closed, the displayed EAR was

1. These observations are consistent with the expected decrease in EAR during eye closure.



Fig. 2. Example open-eye frame (EAR = 0.39) and closed-eye frame (EAR = 0.19) from the implemented vision prototype.

1. GSR processing and prototype sensor fusion The GSR stream is sampled by the ESP32 and transmitted as a sequence of integer ADC readings at 115200 baud. For an initial prototype, the GSR signal is

treated as a relative physiological feature rather than converted directly to a calibrated conductance value. A future version can establish a subject-specific baseline

and use normalized deviations, slopes or phasic responses rather than an absolute ADC threshold.

The intended fusion logic uses the temporal eye-closure condition together with the GSR trend. Because GSR can vary with electrode pressure, skin moisture, movement and individual physiology, a single raw GSR value is not used as a standalone fatigue diagnosis. The system instead presents the two channels as complementary indicators and produces a prototype warning when the configured visual condition is sustained, with GSR available for contextual monitoring.

3. Labview Monitoring Layer

LabVIEW 2022 is used as the supervisory monitoring environment. The intended front panel contains a GSR numeric indicator, a continuously updating GSR waveform chart, eye-status indication, fatigue-status indication, alarm status and a stop control. Serial communication is configured for the ESP32 connection, while Python remains responsible for facial landmark processing. This separation prevents

LabVIEW from having to reproduce the MediaPipe computer-vision pipeline and allows each environment to perform the task for which it is suited.

An active buzzer is available as the physical warning actuator. In the complete prototype, a warning command can be sent to the ESP32 so that the buzzer is activated when the configured fatigue-warning condition is reached. The buzzer is therefore an alert output and not a measurement channel.

4. Experimental Setup

The experimental prototype consists of an R-1085 GSR sensor, an ESP32 development board, a laptop with a built-in RGB camera, a laptop running Python 3.12 with OpenCV and MediaPipe, and LabVIEW 2022. The GSR subsystem was first tested independently to verify that the ESP32 could acquire a changing signal. The camera subsystem was separately tested using the facial landmark and EAR pipeline. This component-wise validation reduces ambiguity when integrating the complete system.

Table 1: Hardware and software components used in the prototype.

Component	Role
R-1085 GSR sensor	Skin-response signal acquisition
ESP32	Analog acquisition and USB serial communication
Laptop RGB camera	Non-contact facial observation
Python + OpenCV	Camera capture and image processing
MediaPipe Face Landmarker	Facial landmark estimation
LabVIEW 2022	Monitoring and visualization layer
Active buzzer	Prototype warning output

5. Results And Discussion

1. GSR sensor test

Two simple conditions were tested using the R-1085 module. In the first condition, the first and second fingers were placed on the two electrodes. Thirty-five consecutive readings were recorded. In the second condition, the fingers were removed and 37 readings were recorded. The resulting statistics are summarized in Table 2.

Table 2: Measured R-1085 GSR ADC values under the two test conditions.

Condition	N	Min	Max	Mean	Std. dev.
Finger contact	35	2242	2270	2262.40	4.75
No finger contact	37	2366	2490	2400.38	23.81

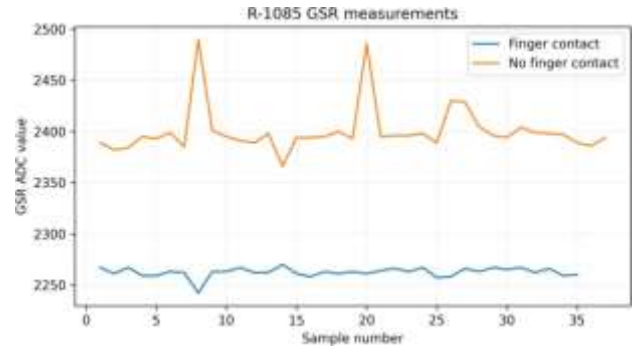


Fig. 3. Recorded GSR measurements for finger-contact and no-contact tests.

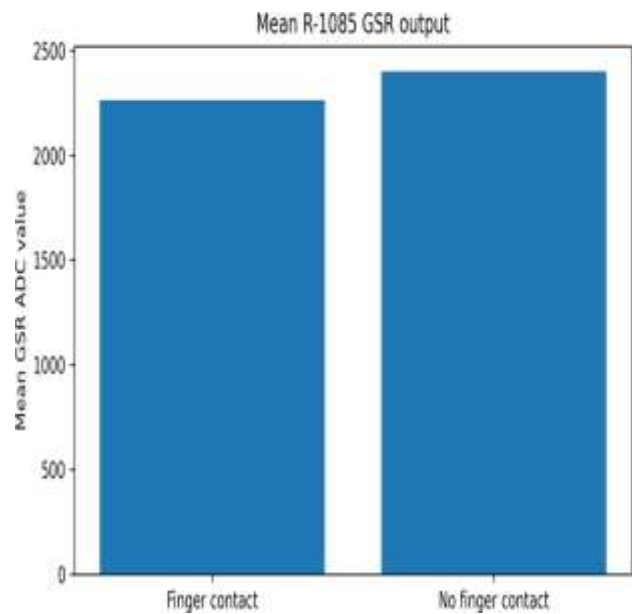


Fig. 4. Mean R-1085 GSR output under the two test conditions.

The finger-contact condition produced a mean of 2262.40 with a standard deviation of 4.75, while the no-contact condition produced a mean of 2400.38 with a standard deviation of 23.81. The difference between the means was approximately 138 ADC counts, corresponding to about 6.1% relative to the finger-contact mean. The result confirms that the prototype produces a measurable change associated with electrode-skin contact. The higher variability in the no-contact condition is also consistent with the fact that the electrodes were not being held in a stable contact condition. These measurements are functional tests of the acquisition chain rather than a fatigue experiment.

6. Vision Test

Observed condition	Measured EAR	Displayed state
Eyes open	0.39	EYES OPEN
Eyes closed	0.19	EYES CLOSED

Table 3: Example EAR observations from the implemented camera prototype.

The captured camera frames demonstrate a clear separation between the example open-eye and closed-eye states: the EAR decreased from 0.39 to

The prototype therefore provides a usable geometric feature for detecting eye closure. However, two still images do not establish fatigue-detection accuracy, sensitivity or specificity. A larger time-series experiment containing normal blinking, prolonged eye closure, different illumination levels and multiple participants is required for those claims.

7. Integrated Monitoring Concept

The integrated system is designed to combine the two channels rather than interpret either one as a definitive fatigue measurement. The vision channel supplies a temporal behavioral indicator, while GSR supplies a physiological signal that can be monitored relative to an individual's baseline. This multimodal approach is consistent with literature emphasizing the potential value of combining behavioral and physiological information, while also recognizing that validation and subject variability remain important issues [1-4,6].

For the current prototype, the most defensible demonstration criterion is prolonged eye closure with simultaneous GSR logging and an available buzzer alert. Future experiments can replace the fixed EAR threshold with subject-specific calibration and a statistical or machine-learning fusion model trained on labeled fatigue states.

IV. LIMITATIONS

The current prototype has several limitations. First, the GSR measurements are raw ESP32 ADC values and have not been converted into a calibrated skin-conductance quantity. Second, GSR is influenced by electrode pressure, moisture, motion and individual physiology. Third, the camera-based EAR measurement depends on

illumination, face orientation, camera position and landmark quality. Fourth, the present results use a very small number of observations and do not constitute a multi-participant fatigue-validation study. Fifth, the prototype warning

threshold is an engineering setting rather than a clinically established criterion.

The system should therefore be considered a research and educational prototype rather than a medical diagnostic or safety-certified fatigue detector. In particular, the current experiments demonstrate sensor operation and visual state discrimination, but they do not establish that the system can reliably determine fatigue in real-world users.

1. Future Work

Future development will focus on subject-specific GSR baseline calibration, longer synchronized recordings, multiple participants and controlled fatigue-state labeling. The vision pipeline can be extended to PERCLOS, blink frequency, yawning and head-pose features. A supervised fusion model can then combine normalized GSR and facial features. Additional work should evaluate performance under different lighting and camera positions and compare results against a suitable behavioral or sleepiness reference measure. Wireless communication, improved electrode ergonomics and additional physiological channels are also possible extensions.

V. CONCLUSION

A low-cost multimodal human fatigue-monitoring prototype was developed using an R-1085 GSR sensor, ESP32, a conventional laptop camera, MediaPipe-based facial landmark analysis, Python and a planned LabVIEW 2022 monitoring layer. The GSR subsystem produced stable finger-contact readings with a mean of 2262.40 and showed a measurable increase in the no-contact condition, while the camera prototype produced EAR values of 0.39 for an example open-eye state and 0.19 for an example closed-eye state. These results verify the basic operation of the two sensing paths. The system provides a practical foundation for multimodal fatigue monitoring, but larger controlled experiments are required before quantitative fatigue-detection performance can be claimed.

1. Acknowledgements

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2. Data Availability

The GSR measurements reported in this paper were collected during the prototype tests described in Section 5. The vision examples are representative screenshots from the implemented camera prototype.

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