Retraction

Retraction: Fatigue Monitoring Using Real-Time Facial Expression Based on Neural Technique (J. Phys.: Conf. Ser. 1916 012116)

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This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1

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Fatigue Monitoring Using Real-Time Facial Expression Based on Neural Technique

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Abstract. The face, as a crucial part of the body, communicates a great deal of information. When a driver is extremely tired, his or her facial expressions, as well as the frequency at which he or she wiggles, vary from those in a normal state. In this paper, we suggest a device that senses the driver's drowsiness and, as a result, triggers an alarm about the vehicle's ordinance and has a tendency to slow down the vehicle. When drowsiness is detected, alarms will sound, the seat will begin to vibrate, and the lights will turn on, all without the use of any sensors. We implement a brand new facetracking algorithm to improve tracking accuracy as a result of the limitations of previous algorithms. We have devised a facial region replacement detection system. Then we use these facial regions to assess the condition of the drivers. Our device will alert the driver by using a fatigue warning by integrating the features of the eyes and mouth. It's a computer vision system that can detect driver drowsiness in an approaching video stream and raise an alert if the driver seems tired.

Keywords: CNN, fatigue detection, face recognition, Image Processing.

1. Introduction:

A rise in demand for modern transportation has necessitated faster car-park development in recent years. The car is now a necessary mode of transportation for most citizens. Globally, 97 million vehicles were sold in 2017, representing a 0.3 percent increase over 2016. In 2018, the total number of vehicles in use worldwide was reported to be over 1 billion[1]. While the car has altered people's lifestyles and made everyday tasks more convenient, 38,572 humans have died and also 4,287,220 humans were physically damaged. Fatigued driving was responsible for roughly 18% to 34% of the traffic incidents in these situations. The method of detecting the driver with drowsiness has been a trendy and famous experimentation subject in recent years. There are two varieties of detecting mechanisms. A motorist should capitivate in the subjective detection method's assessment, which is linked to the driver's subjective expectations by measures including self-questioning, evaluation, and filling out questionnaires.
With its ease of implementation and reduced price, the untouched method has been widely used for detecting the tiredness/sleepiness of the motorist. Perception Techniques and SmartEye, for instance, use the motion of the motorist's eyes to evaluate their level of tiredness/sleepiness.

In this study, we propose using an un-touch method called Driver care to determine tiredness/sleepiness. The motorist does not have to carry any on-body or in-body equipment because our system relies solely on the automobile camera. By using frame photos, our design evaluates and detects the motorist's state.

The motorist's eyes and mouth are extensively used in monitoring. As a result, judging driving fatigue requires recognizing the driver's main facial features. A deep convolutional neural network was proposed in a previous study for detecting key points. Third, determining the degree of drowsiness in the driver is critical for our system. Drowsiness can be seen on people's faces when they are tired.

2. Related work:

This chapter is divided into three segments: optical artifact monitoring algorithms, face image classification algorithms, and motorist detection techniques. Visual bases image object tracking, Visual object recognition is a critical problem in computer vision. They can be used in fields such as artificial intelligence interaction, behavior recognition, robotics, and surveillance, to name a few. Given the first state of the package before the frame, finding the species in each frame of the video frame is measured utilizing visual object tracking.

On the other hand, this algorithm indeed tracks a moderate proportion of objects moving within image sequence frames. In the context of the current evolution of computer design's significant effect on the dependent. To enhance object tracking, [2], colored functionality, and a grid correlation filter-based system were used. To monitor the object, [3] an exclusionary regression filter were used. As the tracking target rotates. Since the creation of the deep-learning algorithm. While these algorithms are more precise than correlation filter-based track algorithms, they require more time to learn. As a result, in the real world, these algorithms are unable to monitor the object in real-time. In this method, the EAR is used to monitor artifacts, and CNN is used to overcome the EAR limitation. As a part of our approach, the algorithm can model the motorist's face in practical systems.

Understand the characteristics of the face, The aim of biometrics and face is to obtain crucial details such as the location of the brows and eyes on the face. It is the first time that human facial key points have been identified thanks to the advancement of deep learning. Although its speed is very high, this algorithm only recognizes 5 for Sun. [4] used to get better performance for facial keypoint recognition, FACE, which prioritizes CNN and can recognize 86 facial key points, was created. However, this algorithm necessitates further modeling and is extremely difficult to implement. Convolutional Neural Networks that have been tweaked (TCNN), Using the Gaussian Mixture Model as a basis, were proposed by Wu to boost different layers of CNN. CNN's robustness, on the other hand, is overly reliant on results. Deep Alignment Network (DAN) was introduced [5] to identify facial key points, and it outperforms other algorithms. Regrettably, DAN necessitates broad models and calculations based on complex functions. Driver Care uses [6] to identify facial key points to fulfill the requirement of real-time results. Drowsiness detection for drivers. There are two forms of approaches for detecting driver drowsiness: touch approaches. Warwick used BioHarness 3 to gather data and assess drowsiness on the driver's body. I used an electroencephalographic (EEG) signal to detect driver drowsiness using a smartwatch. [7] redesigned the vehicle wheel controller
and integrated an irregular heartbeat sensor to detect the driver's signal. Picot also proposed a method for predicting drowsiness using the signal and blinking functionality. Our proposed functionality of the application is shown in figure 1.

![Figure 1. The functionality of the Application.](image-url)

2.1 Driver care overview:
Driver Care is a proposed system that makes use of a commercially available camera car computer. To meet the system's real-time performance, we utilize our method to monitor the motorist's face and identify facial unique resources associated with the identified detection. The cloud server calculates the driver's state as the provinces of the mouth and eye change.

3. Driver face tracking by EAR:

![Figure 2. The image after illumination.](image-url)

![Figure 3. Original Image](image-url)

3.1 PRE-PROCESS
we calculate the gradient orientation and gradient variable “D”. The vertical gradient, and horizontal gradient values at (a, b) are proclaimed by X(a, b), Y(a, b), and Xm(a, b). The picture is then segmented into n cells. According to [8], the gradient orientation is divided into 9 contrast-sensitive bins and 18 contrast-insensitive bins. The value of the orientation bin increases by one if every pixel in a cell belongs to the corresponding orientation. Finally, there are 9-dimensional and 18-dimensional histograms in each cell. Each cell's gradient is determined by the internal pixels as well as the four cells surrounding it. Figures 2 and 3 above mentioned are taken in light and illumination.
The 18-dimensional eigenvector is transformed into a 72-dimensional feature vector, for a total of 108 feature vectors. Then, concerning the matrix of 427, we organize this eigenvector. Finally, we use matrix addition to obtain 31-dimensional HOG features, dubbed the FHOG function.

By squeezing layer encoding, a map of functions of size. We can get a function map from Formula 1 with the dimensions H W (e1 + e3) by expanding the layer.

Multifeature fusion

\[ g_{ij} = (x_i-x_0) \cdot (x_j-x_0) = \frac{1}{2} (||x_i-x_0||^2 + ||x_j-x_0||^2 - ||x_i-x_j||^2) \]  (1)

Figure 4. Dimensional HOG.

As a consequence, the CNN features include a function called dimensional HOG shown in figure 4. The model is being updated to improve the model's system throughput and the platform's time performance, expand the total amount of frames. Because the modified artifacts are tiny in certain frames. Thirds were selected as the value of No of frames.

4 Assessment of the driver’s discomfort:

We’ll go into how the Driver Care System analyses the driver’s face in the eventuality of dizziness in this couple of chapters. A change in the specific condition of the eyes and mouth usually indicates drowsiness.

4.1 DETERMINATION OF THE DRIVER’S FATIGUE

We demonstrate how the condition of the eyes, as well as the condition of the mouth, are used to assess the condition of the driver's fatigue. We suggest a new approach for determining the condition of the eyes that is more accurate than other approaches. The health of the eyes is determined by the angle of the eyes, according to CNN. Driver Care also examines the driver's mouth to see whether he or she is yawning.

4.2. Eye and mouth area determination

We check and manage the man's face at every spectral information. Then, using the Dlib library, we find six main facial features on the person's face. After obtaining the main points, we set the measurements of each key aspect to (Xa, Yb) and use them to identify each location of the mouth and eyes on the person's face shown in Figures 5 and 6.
Figure 5. Detecting the face.

Figure 6. The facial points.

Coordinate X of the ith and jth central points, respectively, are expressed by xi and xj. The Y coordinates of the nth and mth key points are expressed by yn and ym, respectively. In Formula-2 the coordinates of the vertices of the rectangular region of the eye are denoted by lex and ley.

\[
\begin{align*}
\text{lex} &= x_i + x_j/2 \\
\text{ley} &= y_m + y_n - y_m/4
\end{align*}
\]  

(2)

The mouth's width-to-height ratio in various segments.

Based on the rectangular symmetry shown in Figure-7, After collecting the upper and lower eye points, we determine the eye socket region on the motorist's face.

Figure 7. Eye points.

4.3 Recognition of eye status

4.3.1 CNN-based identification

To identify the eight layers of the eye state, we built a CNN.

\[ f(x) = 1/(1 + e^{-x}) \]  

(3)
The range of the result is $[0, 1]$. During preparation, an active eye has a value of 1, indicating positive samples, while a closed eye has a value of 0, indicating random samples. The impact of open eyes is represented by a projected value greater than 0.25 in the fractal dimension nonlinear activation output using Formula-3; otherwise, it reflects eyes closed.

### 4.3.2 Angel-based Recognition

To compensate for CNN's shortcomings in the closure of eye detection, we use the angle of the eye, due to its drawbacks following CNN's confirmation that the motorist's eye is state opened. To double-verify the effect, we use the motorist's side view eye viewing angle. The mechanism by which the eye closes and opens is known as eye movement. The accompanying equation shown in Formula-4 is used to calculate the orientation of the eye considering important elements in the upper eyelid.

\[
d_{ij} = \sqrt{(y_j-y_i)^2 + (x_j-x_i)^2}
\]

\[
A = (\arccos \frac{d_{ab}^2 + d_{ac}^2 - d_{bc}^2}{2d_{ab}d_{ac}}) \times \frac{22}{7} \times 180^0
\]

However, when persons are moderately tired, the volume of flashes increases; however, when people are extremely tiredness/sleepiness, the total amount of lights up decreases. If you blink more than 30 times per minute or less than 6-7 times a minute, you're probably tired.

### 4.3.3 Recognition of the status of the mouth

The features of the mouth are critical for detecting fatigued driving because when a driver is drowsy, he or she will yawn repeatedly. As a result, these features are used by Driver Treatment to assess evaluation performance. In this, To determine the mouth's height-to-width ratio, we obtain some important elements in the mouth. This is how the equation is rewritten:

\[
H = \sqrt{(y_r-y_e)^2 + (x_r-x_e)^2}
\]

\[
W = \sqrt{(y_u-y_v)^2 + (x_u-x_v)^2}
\]

\[
F = \frac{H}{W}
\]

The angulus oris has two coordinates $(x_u, y_u)$ and $(x_v, y_v)$in Formula-5. If $f$ crosses the threshold, Driver Care assumes the driver is opening his or her mouth, and vice versa. As a result, To differentiate between actions like yawning and speaking, we test the time duration proportion $H$ of the widening mouth.

The $f$ of which is greater than the threshold is around 0.025 As a result, The amount of gapping in one minute is counted, and the driver is considered drowsy if he or she gapping more than thrice a minute.

However, notes that when a driver is engaged in dull or repetitive tasks, the frequency of yawning increases. As a result.

### Algorithm for Fatigue Detection Algorithm

Frames from a video are used as input.

if $a > 30\%$ then $Q = 1$ end if
If $v > 3s$ and the individual isn't yawning

$$h_t = 1 \text{ end if}$$

if $c > 0.25$ or $n < 0.25$ then

$$M = 1 \text{ end if if } P = 2 \text{ and so}$$

A motorist is tired/sleepy.

else

A motorist is active.

end if

5. Experiments

It displays a Driver Care prototype that includes a Macbook Laptop with a 2.2 GHz processor and 8 GB of memory to modulate a commercial 360 camera and an Intel Core i3 gen CPU.

Fifteen members collect the video data collected by the automobile lens. Each volunteer alternates between driving while drowsy and awake. Almost every clip is one hour long. To create the application framework in which our experiments will take place. Figure 8 shows the hardware of the implemented system.

![Figure 8](image)

**Figure 8.** The hardware of the implemented system.

5.1 Experimental Analysis

We put Driver Treatment to the test and compared it to other approaches in the same situation.

To test the efficiency of the tracking algorithms, The final experiment is calculated as the average findings in each case.

The EAR algorithm has the highest tracking accuracy. Although the EAR algorithm is the fastest, its accuracy is inferior to that of the EAR and CNN algorithms. The EAR algorithm has the best face image detection performance, about 25 percent higher than the Struck algorithm, but it can only process 30 clips fps, which is so slower than the EAR algorithm. The EAR satisfies our system's requirements. As a result, shown in Graphs 2 and 3, we believe the EAR algorithm outperforms the competition and meets the realistic criteria for speed and accuracy Fig 9,10.
Figure 9. In a complicated environment

Figure 10. In a drive-like environment.

Face tracking precision in multiple settings.

Table-1 Method used for recognizing the eye.

| Method   | The size of the video | The size of the hu | Accuracy | Frames per |
|----------|-----------------------|--------------------|----------|------------|
| MTCNN    | 1280 x 720            | 240 x 300          | 93.2%    | 3 fps      |
| KCF      |                       |                    | 91%      | 188 fps    |
| DSST     |                       |                    | 85%      | 6 fps      |
| Struck   |                       |                    | 76%      | 8 fps      |
| KCF+CNN  |                       |                    | 93%      | 26 fps     |

Methods for recognizing eye state are compared as shown in Table 1.

5.2 Driver Care Performance

When a driver is tired, however, the frequency of blinking and the time it takes for the eyes to close are increased.

Table-2 Comparing the different use cases.

| Number | The driving environment | Detection rate | Frames per second |
|--------|--------------------------|----------------|-------------------|
| 1      | Bright & Glasses         | 92%            | 18                |
| 2      | Bright & No Glasses      | 92.6%          | 18                |
| 3      | Darkness & Glasses       | 91.1%          | 16                |
| 4      | Darkness & No Glasses    | 91.6%          | 16                |

For the time being, there isn't a publicly available image-based driver drowsiness recognition dataset that can be used to estimate the efficiency of our process. As a result of the various datasets, we are unable to equate the efficacy of Driver Care to that of other approaches. As a result, we equate our approach to other
approaches derived from a video-based dataset. Table 2 displays the results. Table 2 shows that, as compared to current methods such as, [9], and [10], Driver Care has an average accuracy of 11% higher than [11]. As a result, the precision of Driver Care is superior to that of other approaches, and Using Figure 11 and 12 Driver Care will satisfy our estimation accuracy requirements.

![Figure 11. A motorist in an Active state.](image1)

![Figure 12. A motorist in sleepy Condition](image2)

6. Conclusion:

Centered on face monitoring and facial keypoint detection. To strengthen the original EAR algorithm, we develop a new algorithm and propose it to monitor the driver's face using CNN. We classify facial recognition. We also present a new drowsiness assessment approach focused on the state including the eyes. As a result of its fast-operating speed, Driver Treatment is almost a real-time machine. According to the results of the tests, Driver Care can be used in several situations and can provide consistent efficiency.

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