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Driver alertness monitoring system in the context of safety increasing and sustainable energy use

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Abstract
Road transport is an important factor in carbon dioxide emissions. These emissions can be reduced by improving propulsion sources and traffic flow (avoiding traffic jams due to accidents). This article presents a system for monitoring and warning the driver to prevent a possible accident involving material damage, injury, or loss of life. The system performs video monitoring of the driver in order to determine his state (tired or attentive). By reducing traffic incidents and traffic jams, the energy consumed will not be wasted; thus, more sustainable transport energy use can be achieved.
Keywords
Driver monitoring, sustainable energy use, drowsy driving, CO_2 emissions.

1. Introduction

Road transport is one of the most energy-intensive sectors compared to other modes of transport: air, rail and water. However, in some situations, car transport is a safe way to move goods and passengers. According to Statista (2023), *Figure 1* shows the percentage by category of CO_2 (carbon dioxide) emissions from all means of transport in 2020.

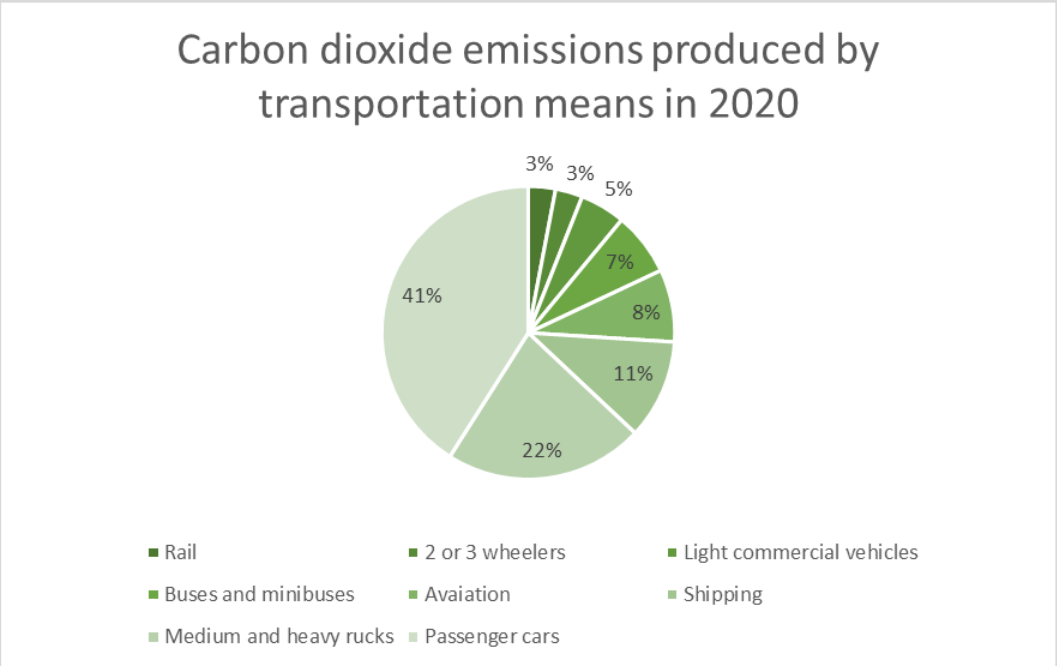

Figure 1 Carbon dioxide emissions produced by transportation means in 2020
(*source: Statista, 2023*)

Although 2020 was the year of the Covid-19 pandemic's onset, industries worldwide reduced their production capacities and the transport sector was directly affected. This did not significantly reduce CO_2 emissions. According to *Statista (2023)*, the approximate total amount of CO_2 emissions due to transport was 7.3 billion metric tons. Population growth in recent

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decades has also increased the number of cars on the road. However, the road and motorway network has not been able to develop so quickly, which causes traffic jams on some roads. Traffic jams in big cities and on motorways are major contributors to transport energy consumption. In this case, we have to consider both the energy gained from fossil fuels in internal combustion engines and electrical energy (stored in the batteries of electrically powered vehicles). Because in these congestions, there is a need for energy consumption which is used both for maintaining passenger comfort (air conditioning + entertainment) and for maintaining the transport conditions of perishable goods. All this energy is practically not used sustainably. It is wasted.

Considering all the losses caused by traffic jams in a single country, more precisely in the European country with the most developed road infrastructure, according to (zf.com), the annual losses to Germany's economy are 80 billion euros. The factors that can generate traffic jams are diverse and numerous (infrastructure maintenance works, traffic light malfunctions, busy road junctions, weather conditions, and accidents). This article will consider traffic jams generated by accidents, particularly accidents due to driver fatigue. It is well known that driver fatigue and falling asleep while driving are relatively common occurrences that result in severe and even fatal accidents.

Several statistics highlight the consequences of driving in a state of severe fatigue. According to NHTSA (National Highway Traffic Safety Administration) statistics, based on police reports, 91,000 crashes were involved or resulted from fatigued drivers in 2017. As a result of these crashes, there were 50,000 injuries and nearly 800 fatalities (*NHTSA, n.d.*). In the following years, the number of fatal accidents due to drowsiness decreased: in 2019, there were 697, and in 2020 there were 633 deaths. According to a study by the Centers for Disease Control and Prevention (CDC), 1 in 25 drivers admitted to falling asleep/sleeping while driving at least once in the past month (*CDC, 2022*). The National Safety Council (*NCS, n.d.*) presents some aspects of fatigued driving. For example, it was found that driving after 20 hours of sleep deprivation would make the driver's actions similar to a driver with a blood alcohol concentration of 0.08%. This can be associated with decreased attention and delayed driving reactions/activities. An Explanatory memorandum (EU, 2021) estimates that between 10 to 25% of all accidents in Europe are due to driver fatigue. Over time it has been observed that fatigue often occurs when driving activities are monotonous. This is most commonly found on motorways and expressways between cities. That is why researchers have been trying to develop different systems to monitor drivers' drowsiness. The solutions investigated have been quite varied, but most have focused on the use of the following sensors: ECG (Electrocardiogram), EEG (Electroencephalogram), EOG (Electrooculography), EMG (Electromyography) and even PPG (PhotoPlethysmoGraphy), which are used in various combinations. Video recorders were also used in most cases. The simple use of these sensors is not enough, so a system is also needed to process all the signals from the sensors so that a decision can be generated on whether the driver is alert or drowsy. To process this data, specific deep learning algorithms (e.g. Fuzzy algorithms) are often used together with ANN (artificial neural networks - (*Liu et al., 2022*).

The main aim of these research projects was to reduce accidents, especially the number of casualties, and to avoid waste due to material damage. In addition to these losses occurring to the vehicles directly involved in the incident, secondary losses generated by the incident must also be considered. A relatively frequent consequence of these accidents is the occurrence of traffic jams which lead to a waste of fuel but can also represent a new accident hazard if they occur on motorways or expressways. Some authors have investigated several variants of complex systems to determine whether the driver is tired. In the following paragraphs, some of these studies will be briefly presented.

In the literature (*Vesselenyi et al., 2009, 2016, 2017, 2019a, 2019b; Nagy et al., 2017, 2018*), several system variants were presented, among which one of the systems was based on the use of EEG, EOG and ECG sensors. These sensors have a good enough accuracy, but a rather inconvenient problem exists. This disadvantage refers to the fact that the sensors must be positioned on the driver's scalp to be as accurate as possible. This was inconvenient and required device calibration for each person, as biological signals can differ from person to person. The system's operation was satisfactory regarding results, but drawbacks arose when mounting the system in the vehicle regarding ergonomics and inconvenience for the driver. Therefore, a video camera was also used, whose images were processed using neural networks based on algorithms. Using the video camera was much easier and less intrusive for the driver, leading to further experiments.

In order to correlate driver monitoring systems developed by different manufacturers or researchers, a common scale with nine levels of attention is usually used. This scale is known as the Karolinska sleepiness scale (KSS) and is presented in Table 1. Of course, just monitoring the driver is not enough. That is why it is also necessary to warn the driver to increase

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his attention. Usually, the warning is done by the following methods: audible, visual and possibly tactile (physical). The warning modes should be correlated with the driver's inactivity, so if the system identifies intense drowsiness, the warning signal will be very strong.

Table 1 Karolinska sleepiness scale

Scale/level:	Description
1	Extremely alert
2	Very alert
3	Alert
4	Fairly alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to keep alert
8	Sleepy, some effort to keep alert
9	Very sleepy, great effort to keep alert

(source: Putilov, Donskaya, 2013)

In order to contribute to traffic safety and reduce energy waste due to accidents caused by driver fatigue, this paper presents a way to process images from the video camera that monitors the driver's actions, especially the driver's face and eye area. In the following sections, some of the research will be described.

2. Data and methods

The algorithm used for face detection is based on the Viola–Jones algorithm (*Viola and Jones, 2001*), which was implemented in MATLAB software. The bounding box is shown in *Figure 2a*. After the bounding box is detected, feature points are selected using a minimum eigenvalue algorithm developed by (*Jianbo and Tomasi, 1994*) (*Figure 2b*):

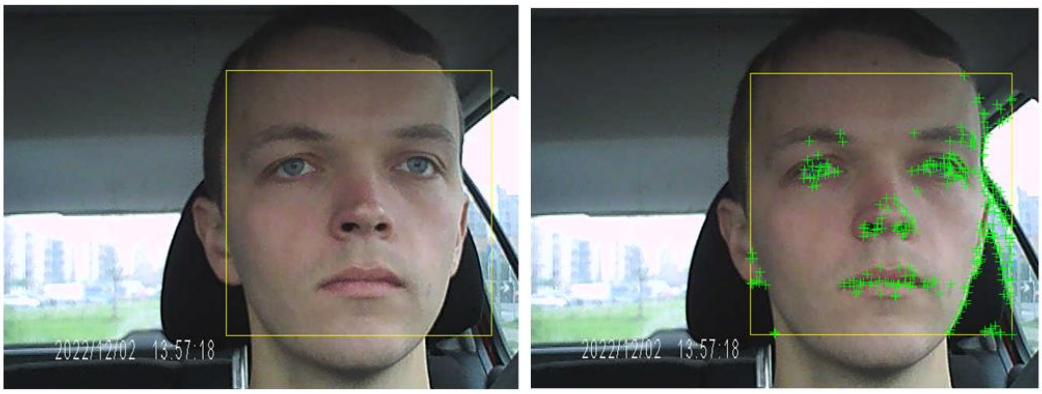

Figure 2a Face detection using bounding box (yellow); b Detected characteristic points (green +).

After detecting the feature points, a tracker algorithm can be applied, such as the Kanade–Lucas–Tomasi (KLT) algorithm (*Tomasi and Kanade, 1991*). The point tracker can be used in a larger program when more detections are needed.

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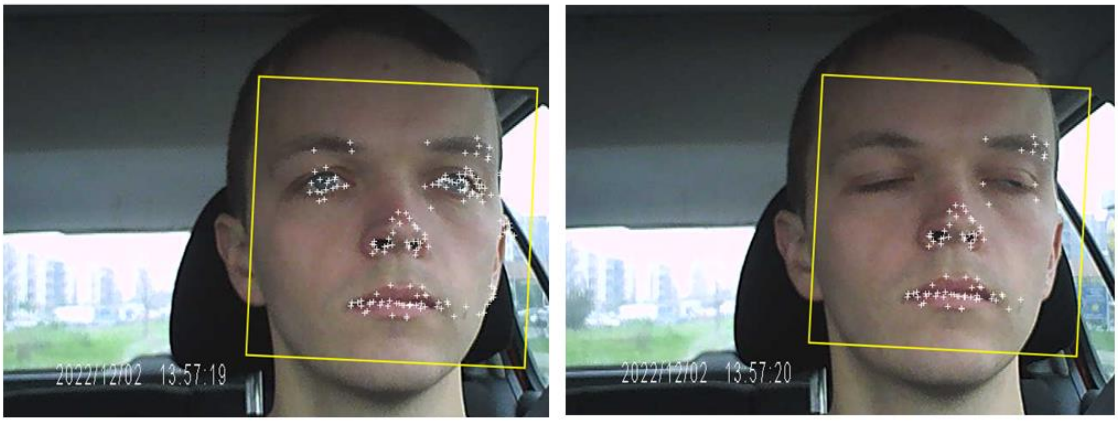

Figure 3a Feature points before blinking; b Loss of feature points after blinking.

Due to lost points, successive acquirements of feature points must be made. This can be observed in Figure 3, where in *Figure 3a*, a large set of points are lost after the driver has blinked (*Figure 3b*). The applied face-tracking algorithm is sufficiently robust to work even in extreme cases (*Figure 4*):

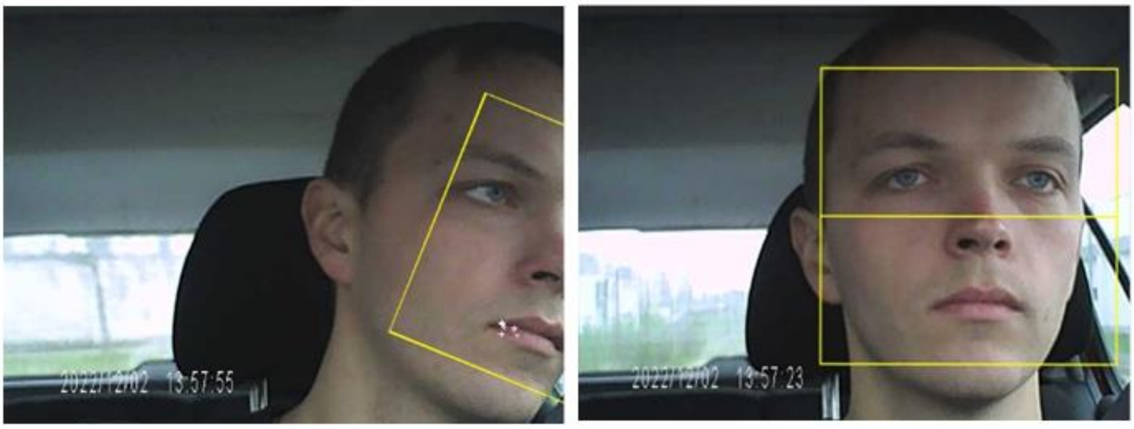

Figure 4a Extreme position of driver's face still detected by the algorithm; b Upper half of the face detection box.

We can use deep learning ANN for eye state detection, like, for example, CNN (Convolutional Neural Network - Kumari, Chakravarthy, 2022). For this study, we used a CNN algorithm which is available in the Deep Learning Toolbox of the Matlab software. The network has been set up with the following structure. The input layer width is computed from the size of the image (in this case, 416× 416 DPI). This is followed by five kernels, each consisting of four layers: convolution, batch normalization, ReLU (Rectified Linear Unit) and max pooling. The Convolution layers have 5 × 5 filters which are growing in numbers from 1 to 64, and the batch normalization units are also growing from 4 to 64 channels. These are succeeded by the last convolution layer 5 × 5 × 64, batch normalization with 128 channels, and ReLU, without a max pooling layer. Instead, the last layers form one fully connected layer, one softmax layer and a Classification Output layer with classes ‘0’ for images with closed and ‘1’ with open eyes. The training set consisted of 100 images for opened and 100 for closed eyes. A sample of 20 images used for training and validation is given in Figure 5:

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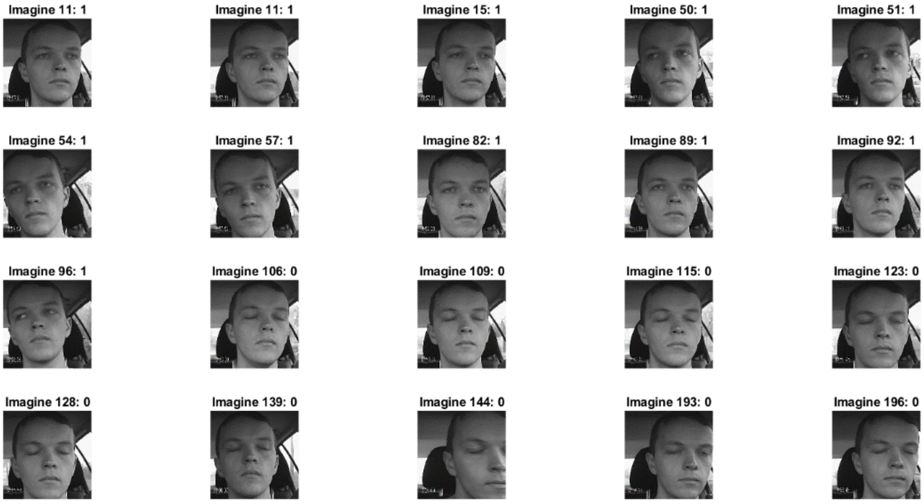

Figure 5 The samples of whole face images used for training and validation.

3. Results and discussion

The results of the training process are given in *Figure 6.* After repeated training sessions, we obtained a maximum classification accuracy of 87.5%.

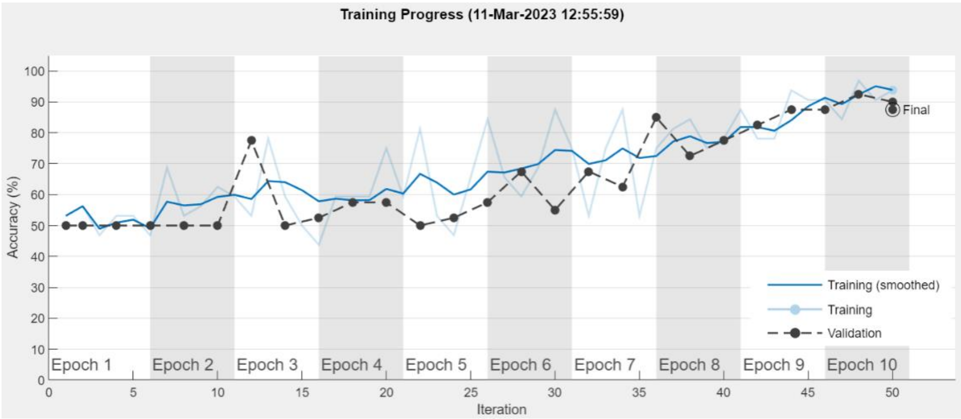

Figure 6. Evolution of accuracy over training epochs for the entire face detection.

In order to improve the accuracy of the classification, we used as input images only the upper half of the previously used whole-face images and trained the same network. We constantly obtained accuracy levels between 97.5 and 100% for successive training sessions. A sample of 20 randomly chosen images is depicted in *Figure 7*, and the evolution of accuracy as the training progresses shown in *Figure 8*.

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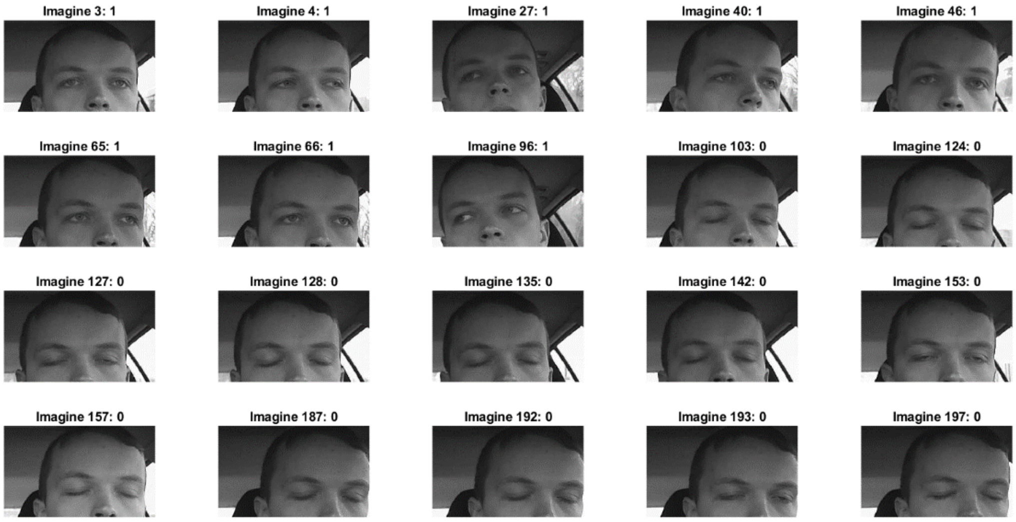

Figure 7. 20 samples of upper half face images used for training and validation.

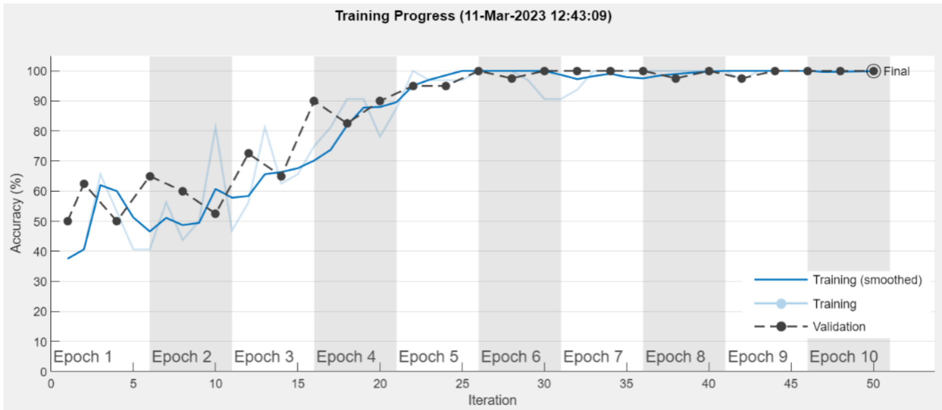

Figure 8. Evolution of accuracy over learning epochs for the upper half face detection.

It could be observed that under optimal brightness conditions and if the neural network has a large enough database for training and learning, the system has increased accuracy in detecting the driver's state. Even if this system, based on video monitoring of the driver's activity, is perhaps the most comfortable, it must have a backup solution in case of malfunctions, which often refers to sensors that must be in contact with the driver. Albadawi et al. (2022) present such hybrid fatigue monitoring systems.

While great strides have been made in autonomous driving, the technology is not sufficiently developed to be relied upon in every driving situation. Considering the levels of autonomy defined by SAE International (*Shuttleworth, 2019*), driver monitoring would be beneficial up to SAE level 3. Thus, implementing such systems to monitor driver fatigue would bring an important benefit to road safety.

For the same reason, several institutes have started to take action on this issue to reduce the number of accidents due to driver fatigue and avoid generating traffic jams and wasting resources. A EURO NCAP document of July 2022 also refers to driver (fatigue) monitoring systems. Moreover, according to Regulation *(EU) 2019/2144* of the European Parliament and the Council, car manufacturers must introduce driver fatigue monitoring systems from 7 July 2024 for all new motor vehicles. The Explanatory Memorandum (*EU, 2021*) sets out much of the technical detail that car manufacturers must consider.

4. Conclusion

In conclusion, the mandatory implementation of fatigue monitoring systems on new vehicles will initially influence the development and implementation costs, increasing the vehicles' production costs. However, the main attributes of such a system will only become apparent after its widespread in vehicle construction. The major expected benefit would be to reduce the high number of accidents (fatalities + material damage) due to driver fatigue or reduce the severity of accidents. Even if the number of accidents were to decrease by only a few percent, it would still be a significant benefit, considering the secondary costs arising from road accidents.

A possible future research direction on this topic would be to test neural network functionalities when brightness conditions are greatly impaired by either strong sunlight or poor cabin illumination.

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