Driver drowsiness detection using ANN image processing

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Abstract. The paper presents a study regarding the possibility to develop a drowsiness detection system for car drivers based on three types of methods: EEG and EOG signal processing and driver image analysis. In previous works the authors have described the researches on the first two methods. In this paper the authors have studied the possibility to detect the drowsy or alert state of the driver based on the images taken during driving and by analyzing the state of the driver’s eyes: opened, half-opened and closed. For this purpose two kinds of artificial neural networks were employed: a 1 hidden layer network and an autoencoder network.

1. Introduction

Car accidents are one of the major causes for injury or death. Statistics show that car accidents are globally the 9th cause of death: 1.3 million people die in car accidents annually, or 3287 per day. Fatigue at the steering wheel has the following symptoms: frequent yawning, hard to keep the eyes opened and to focus on the road, not remembering what happened in the last few minutes of driving, not keeping the correct distance from the car in front, missing traffic signs and getting too close to the side or center of the road.

Statistics have shown that over 10% of accidents are due to fatigue, most of which occur on highways or after driving on a large number of kilometres. The influence of fatigue on accidents has been proven throughout several studies. According to National Highway Traffic Safety Administration (NHTSA), an annually average from 2009 to 2013, there were over 72,000 police-reported crashes involving drowsy drivers, injuring more than 41,000 people, and killing more than 800.

In recent years, car manufacturers have developed systems which aim to reduce all the factors that may lead to accidents. This is how sensors, over-ride warning sensors, the adaptive auto-pilot which keeps a constant distance from the front vehicle and fatigue detection sensors were born. Car manufacturers have studied the possibilities of detecting driver’s fatigue for a long time and, of course, the best solutions for the warning on time. Assistance systems now include different types of equipments that can prevent accidents caused by fatigue:

1. In order to prevent serious accidents due to driving fatigue, the Bosch Group provides drivers with a sleepiness detection system. This system identifies the signs of fatigue, through monitoring the movements of the steering wheel, suggesting drivers to take a break for a time. The necessary information is provided either by the vehicle’s steering system or by the steering wheel angle sensor, which is part of the ESP system. This way, the sleepiness detection system helps to increase safety while driving.

2. Volvo currently equips some of it’s models with a system called Driver Alerts, which is based on recognizing a tired driver driving style, as opposed to that of a fully awake
driver. In order to detect this slightly winding driving pattern, the Swedish system uses a video camera mounted in front of the interior rearview mirror, which constantly transmits the distance between the vehicle and the roadside markings to a computer. When the predetermined limits of the measured oscillations, the driver is warned to take a break, through audio signals, and a coffee break symbol appears on the central display, in order to emphasize the message.

3. “Fatigue assistance” for Mercedes models has the capacity to store data acquired by sensors about the normal reactions of the driver, which can be later compared to eventual unsafe steering actions of the same driver in a state of increased fatigue. The audio and visual warning of the driver can prevent accidents caused by “one second sleep” due to increased fatigue.

2. A concept for a drowsiness detection system

Alternative methods, which have not been tried out on larger scale by the leading automotive companies, that can detect the state of awareness of the driver can be taken into account.

Three of these methods are based on EEG (Electroencephalography) and EOG (Electrooculography) signals measurement and on the eye state (closed or opened) image classification. The EEG method monitors the brain activity through a sensor placed on a specific part of the scalp, the EOG method tracks the eye movements by measuring the signals from the muscles which are acting on the eye and the eye image analysis can monitor the opened or the closed state of the eye. The authors discussed about the development of such a system in [1]. A scheme of the system presented in [1] is shown in figure 1. Each of the methods used in the system has its advantages and disadvantages. For example, the EEG and EOG sensors, electrodes which have to be fixed with a conductive gel and in most devices must transmit the signal by wire, present a major discomfort. Important research in the field of advanced materials and MEMS technology may solve these problems, as for example the use of dry electrodes for EEG, presented in [2].

![Fig. 1. Drowsiness detection system overview.](image)

Developments in this field are supported by efforts to create brain – computer interfaces [3, 4, 5 and 6] for different applications, including devices that help disabled people.

An application of EEG signal acquisition and processing has been presented in [7, 8 and 9]. In this research the central point is to distinguish between low and high alpha rhythm peaks (as shown in figure 2), which can make the difference between alert and drowsy states.
Fig. 2. Power Spectral Density amplitude versus frequency of an EEG signal, with the alpha rhythm peak in the 10-12 Hz frequency domain: a. alert state; b. drowsy state [7].

Fig. 3. Four types of signals recorded from EOG sensors (EOG1, EOG2 and EOG3 in figure 1) for different eye movements (up, down, left and right).

In other researches [10, 11] the authors have analyzed the possibility to use EOG signals acquisitioned from 3 sensors (EOG1, EOG2, EOG3 in figure 1). After pre-processing, four types of different signals were identified, which are shown in figure 3. The combination of these four types of signals gives the information to distinguish between left, right, up and down movements of the eye.
In [10] and [11] the possibilities to apply EEG and EOG signals were analysed to detect driver drowsiness. In the present paper the study was extended to analyze driver drowsiness by image processing.

3. Drowsiness detection using the processing of the driver’s eye images.
For the classification of the driver’s drowsy or alert state, artificial neural networks were used. Artificial neural networks are extensively used for the image classification in the last decades. A new paradigm named Deep Learning has been developed in [12] and [13] and in many other researches. Deep Belief Networks, Restricted Boltzmann Machines and Deep Autoencoders are all methods belonging to the Deep Learning paradigm. These methods are used in a wide range of applications, the image classification being one of the fields in which these are employed with success. For the study presented in this paper, Matlab Neural Network Toolbox with 1 layer ANN and the autoencoder module of the Deep Learning Toolbox were used in order to study if these methods can be applied for image classification of the driver’s drowsiness. As a premise, it was assumed that the drowsiness is linked to the images in which the driver has closed eyes and the alert state is linked to the images in which the driver has opened eyes. This module had been used for the analysis [14].

In order to analyze the drowsiness state of the driver 200 images of a driver during a regular driving process were acquisitioned. One hundred of these images contain opened eyes or half opened eyes images and another hundred of the images contain closed eyes images. Examples of these images are presented in figure 4.

In order to avoid memory overload and large processing times, the images had been cropped and down-sampled in order to have a smaller amount of input data for the neural networks (figure 5).

![](image)

Fig. 4. Images of a driver with: a. opened eyes; b. half opened eyes; c. closed eyes.

![](image)

Fig. 5. Cropped images of the driver with opened (a) and closed (c) eyes. Cropped and down-sampled images of the driver with opened (b) and closed (d) eyes.

The down-sampling of the images has produced more unclear images (figure 5, b and d), which ensures a more robust classification. If the network works properly for the down-sampled images, it will surely work well for the initial images.
3.1. One Hidden Layer Artificial Neural Network

Following the acquisition of 200 images, 140 of these had been used to train, validate and test the neural network: 70 with opened eyes or half-opened eyes and 70 with closed eyes. The rest of the images (30 for opened eyes or half-opened eyes and 30 for closed eyes) were kept for testing the network after the completion of the training process. The network was trained with the structure presented in figure 6 (2601 neurons in the input layer, 10 neurons in the hidden layer and 2 neurons in the output layer). The number of neurons in the input layer corresponds to the number of elements of the input vector which is the one column reshaped version of the down-sampled image of the driver (represented by a 51x51 elements gray level matrix). The number of neurons in the output layer corresponds to the number of possible categories in which an image can be classified (2 categories: drowsy or alert).

![Fig. 6. Network structure for the 1 hidden layer network.](image)

During the training process the training performance diagram (figure 7.a.) and the error histogram (figure 7.b.) of the trained network were obtained. It can be observe that the training performance reaches values of under 10⁻⁶ at 25 epochs and the histogram boundaries are in a range of -1.5x10⁻⁶ and 1.46x10⁻⁴, which are very good results.

![Fig. 7. Performance diagram (a) and error histogram (b) of the trained network.](image)

More significant, one can observe the results of training, validation and testing presented in figure 8 in the form of a confusion matrix. In a confusion matrix, each column represents a predicted class while each row represents an actual class. The green squares represent the correctly classified and the red squares represent the incorrectly classified samples. There can be seen that each sample has been correctly classified.
3.2. Deep learning Autoencoder neural networks

For the autoencoder network the same input and target vectors as in the case of 1 hidden layer network were used. Autoencoders use methods to separately train each layer, then stack them together in a single network with multiple layers and train the final network as a whole. The network structure is presented in figure 9.

The results of the autoencoder’s training are shown in figure 10. In figure 10.a. the training performance is presented when it reached the value of less than 0.034 (the smaller the better) after 438 epochs. In figure 10.b. the test results show that no false positives or false negatives had been obtained. This means that every test image (60 images – 30 for each class) has been correctly classified.
4. Conclusions

Analyzing the results of applying these networks on the acquisitioned images it can be concluded that both networks had very good results, with 100% positive classification results, which were presented in chapter 3. The small number of neurons used in the hidden layers to successfully classify the images (10 for the 1 hidden layer network and 15 for the autoencoder network) allows the implementation of these networks on compact computing devices, using a very small portion of their memory. Also the processing time is in the order of milliseconds on a Windows based computer, which on a compact device can be more reduced. The training of the network can be done specifically for each driver, thus enhancing the classification success rate.

In future works the authors intend to study the possibility to apply neural network classifiers on more different images, with different drivers, in different positions and lighting conditions. Also the elimination of the cropping and down sampling stages of the image processing will be a goal for future research.

References
[1] Tiberiu Vesselenyi, Alexandru Rus, Tudor Mitran, Bogdan Tataru, Ovidiu Moldovan, VEHICLE DRIVER DROWSINESS MONITORING AND WARNING SYSTEM; 12th International Congress of Automotive and Transport Engineering (CONAT), Brasov, 2016; pag. 873-880.
[2] Sullivan, T.J., Deiss, S.R., Jung, T.P., Cauwenberghs, B., A Brain-Machine Interface using Dry-Contact, Low-Noise EEG Sensors, 2008 IEEE International Symposium on Circuits and Systems Washington, US, 2008
[3] Janis J Daly, Jonathan R., Wolpaw, Brain–Computer Interfaces in Neurological Rehabilitation, Vol. 7, Issue 11, pp. 1032-1043, 2008.
[4] Ting, Jo-Anne, D’Souza, A., Yamamoto, K., Yoshioka, T., Hoffman, Donna, Kakeif, S., Sergio, L., Kalaska, J., Kawato, M., Strick, P., Schaal, S., Variational Bayesian least squares: An application to brain –machine interface data, Neural Networks, Vol. 21, Issue 8, pp. 1112-1131, 2008.
[5] Ting, Jo-Anne, D’Souza, A., Yamamoto, K., Yoshioka, T., Hoffman, Donna, Kakeif, S., Sergio, L., Kalaska, J., Kawato, M., Strick, P., Schaal, S., Variational Bayesian least squares: An application to brain –machine interface data, Neural Networks, Vol. 21, Issue 8, pp. 1112-1131, 2008
[6] Cvetkovic, D., Übeyli, E.D., Cosic, I., Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures: A pilot study. Digital Signal
Processing, Vol. 18, Issue 5, pp. 861-874, 2008.

[7] Ting, W., Guo-zheng, Y., Bang-hua, Y., Hong, S., EEG feature extraction based on wavelet packet decomposition for brain computer interface, Measurement, Vol. 41, Issue 6, pp. 618-622, 2008.

[8] Dzitac, I., Vesselenyi, T., Tarca, R. C., Identification of ERD using Fuzzy Inference Systems for Brain Computer Interface, International Journal of Computers Communications & Control, Vol. 6 Issue 3, ISSN 1841-9836, pp. 403-417, 2011.

[9] Dzitac, S., Vesselenyi, T., Popper, L., Moga, I., Secui, C., D. Fuzzy Algorithm for Human Drowsiness Detection Devices, Studies in Informatics and Control, Vol. 19, Issue 4, ISSN 1220-1766, pp. 419-426, 2010.

[10] Vesselenyi, T., Dzitac, I., Dzitac, S., Hora, C., Porumb, C. Preliminary Issues on Brain-Machine Contextual Communication Structure Development, IEEE Conference, 3rd International Workshop on Soft Computing Applications, Szeged, Hungary, pp. 35-40, 2009.

[11] R. B. Nagy, T. Vesselenyi, F. Popentiu-Vladinescu, “Research on recording and filtering electromyogram (EMG) signals,” in Nonconventional Technologies Review, 2015, pp. 21-25.

[12] Robert-Bela Nagy, Popentiu-Vladinescu Florin, Vesselenyi Tiberiu, AN ANALYSIS OF ELECTRO-OCULOGRAM SIGNALS PROCESSING USING AN ARTIFICIAL NEURAL NETWORK, International Scientific Conference - eLearning and Software for Education, 2017, Volume 3, DOI: 10.12753/2066-026X-17-257, Pages: 560-567, 2017.

[13] G. E. Hinton, S. Osindero, and Y.-W. Teh. “A fast learning algorithm for deep belief nets,” in Neural computation 18, 2006, pp. 1527-1554.

[14] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle. “Greedy layer-wise training of deep networks,” in Advances in Neural Information Processing Systems, 2007.

[15] ***. MATLAB. – Mathworks, Users Manual, Neural Network Toolbox, Deep Learning, Autoencoders, 2016.

[16] ***. National Highway Traffic Safety Administration - Drowsy Driving Research and Program Plan, March 2016