International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 14 (2018) pp. 11582-11588

Driver Fatigue Detection with Time-Feedback Neural Network

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Abstract

This article presents a monitored alert system for the detection of driver fatigue using artificial intelligence techniques based on image processing for extraction of visual features and neural networks for classification. The visual features of fatigue is focused on the detection of eye closure states, nodding and yawning, where these parameters are entered to a neural network with time-feedback of states, generating alert or critical outputs in the classification of the fatigue state. Almost 91% accuracy in detection is obtained by evaluating 10 videos of users in front of the steering wheel, which exhibit fatigue characteristics.

Keywords: Machine intelligence, fatigue detection, neural network, pattern recognition, computer vision.

INTRODUCTION

According to the world health organization, traffic accidents are declared a public health problem. The rates allow to estimate more than one million deaths around the world [1]. Since human lives are not the only loss factor, the material damages in vehicles, road infrastructure or buildings are added to the list of tragedies derived from this problem, evidencing the great magnitude of the same.

The analysis derived from these accidents become investigations that seek to mitigate this problem, allowing to emphasize effects as behaviors when driving in states of anger, as it is presented in [2], and offering a critical point of view against the causes that originate a vehicular accident. Faced with this problem, vehicles equipped with technological systems allow to address solutions that support the work of the driver from different fronts, for example, in [3], derived from the decrease in reaction capacities that occur with age, it is presented a vehicle with advanced technologies oriented to support elderly people in the 60-85 age range, generating safety schemes for driving assistance.

Other research related to the aforementioned problems establish the relationships that most affect drivers and co-drivers in vehicular accidents, as discussed in [4]. In summary, there is a strong interest in providing solutions from research to make the driving task a less incident factor in the cost of human lives.

From engineering applications, many pattern recognition tools have been developed, so that distinguishing patterns of risk in driving can be solved by such tools. Therefore, the present investigation addresses a solution to the problems of vehicular accident that distinguishes patterns of fatigue in the driver, generating alerts that allow him to become aware of the implicit risk factor of continuing to drive in the detected state.

Next, the article describes the algorithms used for the identification of the fatigue state. In section 2, a revision of the state of the art is done, section 3 discusses the proposed work and the image processing algorithms that originate the inputs of the neural network are presented, in section 4 the training and architecture parameters of the neural network are presented, with the results obtained and in section 5 the conclusions

RELATED RESEARCH REVIEW

In the last decades, the algorithms of computer vision have allowed the development of multiple applications in the field of process automation. Among these fields of application are distinguished the developments in robotic systems [5], which allow them to be able to see and take actions to move in a medium [6], [7]. However, the applications of such algorithms are expanded to fields with the interaction with people, for example for medical [8] or security purposes [9].

Within this latter field, many image processing algorithms focused on the detection of fatigue states in conductors have been addressed, due to their evident incidence in the care of human life. Developments such as those presented in [9] and [10] offer a solution to this problem but from an invasive point of view in the driver, where it is necessary to put in the user the sensors of capture of electromyographic information, an impractical aspect in conventional driving systems. Because of this it is necessary to look for alternatives for safe driving based on driver fatigue [11].

This is where image processing systems become relevant, in [12] a computer vision system is presented for discrimination of fatigue state in drivers, where the computer vision system includes not only image processing algorithms but also pattern recognition algorithms, for instance, the case presented in [13]. However, these systems need to take into account the temporal perception of the fatigue state, for example, the analysis based on the recognition of the state of the eye [14], a person who initiates a sleep episode starts to close the eyes, however the blinking is a natural and necessary action of ocular lubrication, which should not generate confusion or false alarms [15]. It is for this reason that the present article proposes a neuronal architecture with time-feedback as a support to the image processing techniques based on the extraction of features in a particular moment of capture of the scene of the driver behind the steering wheel, without losing the temporal relation of the state that was exhibiting the driver.

Within the image recognition schemes, those that use information coding, corresponding to the characteristics of a particular class, allow to optimize the identification processes. Such is the case of Haar classifiers, which encode the existence of contrasts oriented between regions in an image. For example, a set of these characteristics can be used to encode the contrasts exhibited by a human face and its spatial relationships, to extract the features of fatigue. P. Viola and M. Jones [16] implemented a fast method of detecting objects based on a cascade algorithm using the Haar descriptors, which can be calculated by an intermediate representation called an integral image. This method presents a classifier of faces highly efficient and of fast convergence once trained, which is the basis of this development and is already implemented in multiple software tools, so it will not be delved into it.

The driver's sleep recognition systems increasingly support intelligent algorithms equipped in vehicles [17][18], so that they can be embedded within the on-board computer [19] supporting real-time execution [20] and so robust that it does not matter if the driver wears glasses [21], a factor that at some point becomes a limitation for the recognition of eyes by machine vision algorithms. Although the developments in the detection of this state of drowsiness are extensive [22][23][24], the detection modalities present variations that exhibit complements of some algorithms to others, where basic techniques like the mentioned Viola-Jones algorithm continue being base of the detection [25].

Semi-assisted or intelligent vehicles must have the ability to discriminate those conditions that lead to decisions to ensure the integrity of drivers and passengers. In this field the detection of driver fatigue plays a fundamental part [26][27], both integrated in the vehicle and in other mobile support systems [28].

PROPOSED WORK

FEATURE EXTRACTION

Once obtained the identification of the face region using the Viola-Jones algorithm, it is feasible to segment the regions of the face, based on studies of facial anthropometry reported in the literature [29], [30], which present the standard measures of Figure 1, setting two regions of interest (ROI) corresponding to the eyes and mouth. From these regions can be determined a state of fatigue, by basic characteristics such as eye closure, nodding and yawning.

On the ROI of the eyes, which can be seen in Figure 2, which is in conventional color scale with R, G and B channels, it is grayscale by Eq. (1) and a histogram-based thresholding is applied, varying according to the left eye (O_i) or the right eye (O_d), due to the incidence of non-uniform light on the face, as seen in Figure 3.

$$gray = (0{,}299R + 0{,}587G + 0{,}114B) \quad (1)$$

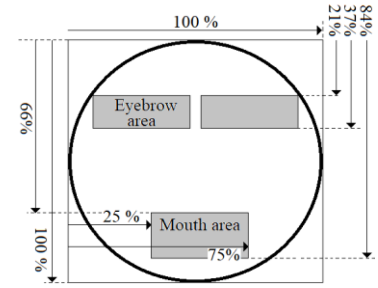

Figure 1. Face Geometry

Figure 2. ROI of the eye

Figure 3. Thresholding of the ROI of the eye.

The initial classification of the opening/closing state of the eye can be performed by setting the significant points of the eye contour, which are taken as: left end (y_i), right end (y_d), upper central point (x_s) and lower central point (x_i), as illustrated in Figure 4. Where the distance $|x_s - x_i|$ allows to discriminate the opening/closing ratio of each eye according to Eq. (2), as an average of the opening value of each eye relative to the calculated maximum aperture.

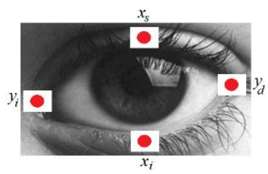

Figure 4. Points of interest of the eye

$$Eye_{close}\begin{cases}1 & if \quad \dfrac{|x_s - x_i|O_d + |x_s - x_i|O_i}{2} < 0{,}4 \cdot |x_s - x_i|max \\ 0 & if \quad no\end{cases} \quad (2)$$

For yaw detection, a color space transformation of RGB to YC_bC_r is applied to the ROI of the mouth, by Eq. (3), in order to emphasize the pronounced reddish characteristics of the mouth from the face of the component C_r, on this component an adaptive threshold is made due to the changes in intensity level presented by the different pigmentations in the skin of each person [31], as can be seen in figure 4.

$$Cr = 128 + 112R - 93{,}786G - 18{,}214B \quad (3)$$

To determine the yawn, the mouth width is set as the difference between the distance of the upper and lower contour. The different widths obtained in the used test images were averaged in order to obtain a fixed threshold for yawn discrimination, in case this threshold resulted in 14 pixels.

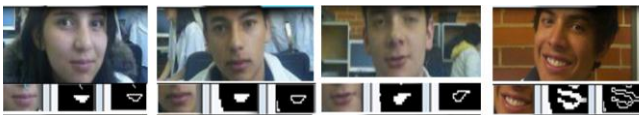

Fig. 4. Red Distance Detection.

The detection of nodding associated with a fatigue state is related to head-settling movements, in which the relative position of the head changes abruptly downwards. For the above reason it is not feasible to validate this change frame to frame, since the variation of said position will not be significant and is susceptible of being confused with another movement.

The nodding detection is determined by a pixel P_i of an initial relative position of the head, conformed by the coordinates P_{ix} and P_{iy}, given by the mean value of the distance between the ROI of the eye area. From a frame of $t = 0$, a frame count of 1 second duration is performed, so that the new position of the head will be P_f. If the difference $P_f - P_i$ exceeds a given threshold, which depends on the resolution of the camera and the distance from the driver, the presence of a nodding is considered, as indicated in Eq. (4).

$$Nodding\begin{cases}1, if\ \Delta(Pf - Pi) > Tresh.in\ t = 1\ s \\ 0, if\ \Delta(Pf - Pi) < Tresh.in\ t = 1\ s\end{cases} \quad (4)$$

CLASSIFICATION STAGE

In order to avoid alarm conditions due to the detection of closed eyes, by normal lashing, whose normal duration is from 100 to 130 ms, an eye closure of more than 200 ms is considered a state of alert, and in order for the system to have an early but assertive response, it must be aware of the previous states as much as possible. In order to determine the number of states to be considered, it is possible to validate up to 3 states without reaching the 200 ms threshold, operating at a processing speed of 50 ms per frame for the extraction of characteristics, this would be reflected by the current frame and the response of two previous frames.

Hence it would be necessary to generate a training base in which these characteristics are included as part of the inputs of the neuronal network with feedback, it has as a first instance that the current frame will follow the characterization according to Table 1, which presents the possible cases to be detected, for example, yawning derived from fatigue and as a response to stress [59], is typically accompanied by eye closure, a speech state that is mistakenly classified as yawning may coincide with a blink, generating a critical false positive, so that only 3.1 and 3.2 cases are really critical, see Table 1 and generating case 2.3 as an alert. The feedback states provide the accumulation of one or two alarm states that can lead to an alert or critical state, which, depending on a single frame, generates the false positive conditions or does not generate the most adequate alarm condition. Similarly, the accumulation of a warning state as condition 2.2 will maintain an alert condition up to two frames but will generate a critical condition with a greater accumulation of this condition, evidencing the importance of the temporal perception.

Table 1. Classification conditions at a time t

	Input			Output
CASE	Closed Eye	Yawning	Nodding	Fatigue
1.1	No	No	No	No
1.2	No	No	Yes	No
1.3	No	Yes	No	No
2.1	No	Yes	Yes	Alert
2.2	Yes	No	No	Alert
2.3	Yes	Yes	No	Alert
3.1	Yes	No	Yes	Critical
3.2	Yes	Yes	Yes	Critical

In Table 2 some of these characteristic states are presented as a function of the feedback according to their relevance.

In example 1, the classification by means of Table 2 sets a state of alert in the current frame and which is reinforced by the previous state of alert of state one, state two does not influence the output response. In example 2, it has the same alert time result which generate a current critical condition to the output by accumulation, this case can be generated by a pronounced eye closure tending to microsleep or a yawn with closed eyes continuous, this case represents a refinement in the training vector with respect to the state of fatigue not possible without feedback. Example 3 represents a state in which after a critical fatigue episode such as pronounced nodding, it is feasible the loss of face location and therefore of the eye measurement and nodding, where it results in retaining a state of alarm and avoiding a false response due to lack of data. Example 4 sets a fatigue recovery effect or simpler even a somewhat pronounced and non-incident eye closure in relation to fatigue. Example 5 presents a non-coherent situation in which a critical state is detected followed by a state of non-fatigue and again critical in the current frame, this would indicate more a loss of the measurement or error of the classification by which the network is trained to sustain the critical state. Example 6 again generates a critical alarm based on the accumulation of previous alert states. Example 7 replicates the condition of Example 5, under the same type of alarm in the current frame, but with respect to a different condition. Examples 8 and 9 show the transition of previous alarm states with a current non-fatigue state, due to the previous state (state $t-1$) that reports a critical alarm, the result of the current frame is smoothed, generating the intermediate alert state.

Table 2. Classification conditions with feedback at time t, $t-1$ y $t-2$.

Example	State $t-2$	State $t-1$	Current State (t)			Output
			Closed Eye	Yawning	Nodding	
1	No fatigue	Alert	Yes	No	No	Alert
2	Alert	Alert	Yes	No	No	Critical
3	Critical	Alert	No	No	No	Alert
4	Alert	Alert	No	No	No	No
5	Critical	No fatigue	Yes	No	Yes	Critical
6	Alert	Alert	No	Yes	Yes	Critical
7	Critical	No fatigue	Yes	No	Yes	Critical
8	Critical	Critical	No	No	No	Alert
9	Alert	Critical	No	No	No	Alert

The structure of the neural network with state feedback to be implemented is of the three layer multilayer perceptron type: input, output and a hidden layer. The input layer is composed of six neurons, given the number of characteristics for setting the state of fatigue, eye opening, opening of the mouth, magnitude of head movement and angle of movement (calculated by Pythagoras), plus the feedback from the two previous states. These six parameters determine the training input vector (60%), validation (20%) and prediction (20%). The output layer allows to determine each of the set states, i.e. normal, alert and critical, in order to simplify the structure of the network is coded in this case according to Table 3, so that 2 neurons are required in the output layer.

Table 3. Final classification codification

Codification		State
0	0	Does not Register
0	1	Normal
1	0	Alert
1	1	Critical

Newly for the hidden layer, the number of optimal neurons is set according to the performance that it presents by subjecting iteratively to the training and validation database, it has a critical point with 60 neurons and it does not present a slightly better result but until a number of 140 neurons. Having between the two points of consideration a difference of more than double the number of neurons by reason of a 7% improvement in the error, reason why it is not justified to increase unnecessarily the complexity of the network, which will also increase the final prediction time, finally opting for 60 neurons in the hidden layer. The neural architecture employed has the form illustrated in Figure 5.

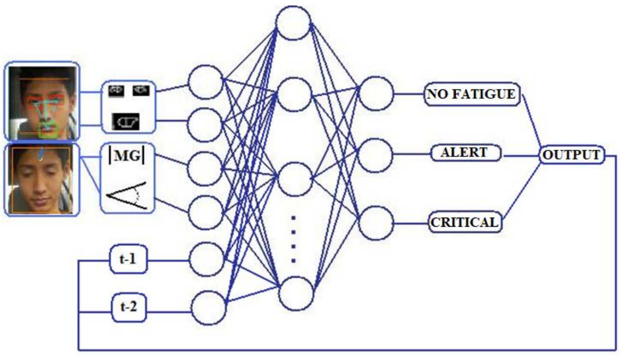

Figure 5. Neural architecture used.

The number of iterations or epochs required to reach an adequate training, according to the presented error rate, was achieved after the 200 iterations, at which point the validation error does not change significantly.

SIMULATION AND ANALYSIS

In order to be able to validate the performance of the chosen structure of the neural classifier, the respective confusion matrices are made that allow to evaluate the performance of the system in a group of 10 videos of short duration (approximately 3 minutes), for 10 different users in front of the steering wheel. In tables 4 to 7, the most representative cases of Table 1 are presented based on the time-feedback, where TP corresponds to the true positives, i.e., the cases in which it is presented and aptly detects said state, FP corresponds to false positives, in other words, to the cases a state is not present but is detected erroneously, and the accuracy reached (ACC).

Table 4. State of fatigue reported for case 2.1

Video	1	2	3	4	5	6	7	8	9	10	TOTAL
TP	2	3	1	2	1	2	3	4	2	3	23
FP	0	1	0	0	0	0	1	1	0	0	3
ACC	100	75	100	66.6	100	100	75	80	100	100	88.4

Table 5. State of fatigue reported for case 2.2

Video	1	2	3	4	5	6	7	8	9	10	TOTAL
TP	20	26	21	24	25	21	19	21	26	22	225
FP	2	1	2	1	1	3	2	2	3	2	19
ACC	90,9	96,3	91,3	96	96,1	87,5	90,4	91,3	89,6	91,6	92,21

Table 6. State of fatigue reported for case 3.1

Video	1	2	3	4	5	6	7	8	9	10	TOTAL
TP	6	6	5	5	6	6	5	5	7	6	57
FP	1	0	0	0	1	1	1	2	0	1	7
ACC	85,7	100	100	100	85,7	85,7	83,3	71,42	100	85,7	89

Table 7. State of fatigue reported for case 3.2

Video	1	2	3	4	5	6	7	8	9	10	TOTAL
TP	3	2	4	2	2	4	2	5	4	1	29
FP	0	0	0	0	0	1	0	1	1	0	3
ACC	100	100	100	100	100	80	100	83	80	100	90,6

It is observed that the general accuracy is 90%, highlighting the fact that the critical cases are being found in their entirety and the system response to these critical cases improves and it is more consistent with the state presented by the driver. Although it is evidenced that false alarms are detected, it does not go against the performance of the algorithm, in relation to the alert of the driver.

Figure 6 shows the graphical result of the feedback network in the algorithm for video 1. In the first image there is a nodding sequence that starts with sporadic eye closures until it reaches the nodding, where it is denoted not to generate excessive alarms. In the second, there are prolonged eye closures that derive in a critical state, the third image shows a prolonged non-fatigue state with an initial blink detection during at least two consecutive frames, the final image denotes several consecutive nodding episodes, where red represents critical and purple alertness.

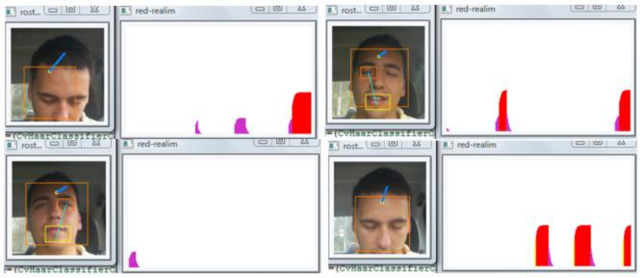

Figure 6. Graphical response of the network.

Table 8 illustrates the overall performance of the network for all alert and critical cases, where it is observed that the final precision reached with the test videos is 90%.

Table 8. Final network accuracy

Neural network with time-feedback											
Video	1	2	3	4	5	6	7	8	9	10	TOTAL
Total TP	39	48	38	42	41	43	37	45	48	43	424
Total FP	4	3	2	3	3	6	4	8	5	4	42
ACC	90,7	94,1	95	93,3	93,1	87,7	90,2	84,91	90,57	91,49	90,99

CONCLUSIONS

It was possible to implement an algorithm of identification of fatigue states in a driver with a high efficiency, taking as reference the time dimension that requires the analysis of said state, evidencing the benefits of this contribution against the developments found in the state of the art, through the use of recurrent neural networks, where the performance increase compared to recognition techniques by means of conventional neural networks, in favor of the reduction of alarms detecting the states of interest.

Given the various tasks of the algorithm, face detection, feature extraction and classification, it works at 20 frames per second, below the rate of a conventional video (30 fps), without affecting the final result, regarding the consideration of fatigue times visually detectable and that may be vital to prevent an accident. This processing time is based on the use of non-dedicated computing equipment, so it allows projection of the replication of these algorithms to embedded systems or on-board computers in semi-assisted vehicles with real-time operation.

The performance of the algorithm is subject to little variant daylight conditions, which limits its application. The tests performed are demarcated in daytime slots in the range of 7 a.m. to 5 p.m. with normal daylight conditions. It requires a complement to the algorithm for its generality in any driving condition, a problem that could be solved under detection algorithms in more robust images such as convolutional neural networks, based on image acquisitions with infrared light.

ACKNOWLEDGMENT

The research for this paper was supported by Davinci research Group of Nueva Granada Military University.

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