Supporting Driver Physical State Estimation by Means of Thermal Image Processing

Paweł Forczmański[0000−0002−3618−9146]
and Anton Smoliński[0000−0003−2216−8114]

West Pomeranian University of Technology, Szczecin, Faculty of Computer Science and Information Technology, Żołnierska Str. 49, 71–210 Szczecin, Poland
{pforczmanski,ansmolinski}@wi.zut.edu.pl

Abstract. In the paper we address a problem of estimating a physical state of an observed person by means of analysing facial portrait captured in thermal spectrum. The algorithm consists of facial regions detection combined with tracking and individual features classification. We focus on eyes and mouth state estimation. The detectors are based on Haar-like features and AdaBoost, previously applied to visible-band images. Returned face region is subject to eyes and mouth detection. Further, extracted regions are filtered using Gabor filter bank and the resultant features are classified. Finally, classifiers' responses are integrated and the decision about driver's physical state is taken. By using thermal image we are able to capture eyes and mouth states in very adverse lighting conditions, in contrast to the visible-light approaches. Experiments performed on manually annotated video sequences have shown that the proposed approach is accurate and can be a part of current Advanced Driver Assistant Systems.

Keywords: thermal imaging · face detection · eyes detection · mouth detection · Haar-like features · Gabor filtering · drowsiness estimation

1 Introduction

Most traffic accidents, according to the road safety research [33], come as a result of drivers' behaviour, often associated with fatigue and drowsiness [29]. According to [32], approximately 20% of accidents are caused by loss of concentration hindering drivers in terms of immediate and right decisions [19]. A majority of techniques aimed at driver fatigue assessment is based on an analysis of signals captured by external sensors that are carried by observed persons. On the other hand, there is also an alternative possibility to perform a continuous observation of the driver without his/her cooperation - it is often realized by machine vision techniques applied to video streams captured in the cabin. The research [19] show that some characteristic behaviours are associated with different activity of head, eyelids and mouth [9].

In this paper we present a research devoted to the methodology for acquiring, integrating and analysing selected visual data in the context of assessing

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

the psychophysical state and the degree of fatigue of drivers or operators of motor vehicles. The proposed algorithm is based on the analysis of visual premises captured in uncontrolled environmental conditions (e.g. in severe lighting conditions or in complete darkness) [20]. While there are many algorithms that are able to detect driver fatigue and drowsiness based on eyes state and blink analysis (e.g. [8, 19, 24]), they work in visible light, or in infrared band, only. It should be noted, that during travelling, drivers encounter dynamic lighting conditions (blinding sun, low-level ambient illumination) and various environmental conditions impairing the observation (e.g. passing through a shaded forest or dark tunnel). Hence, the obvious weaknesses of traditional imaging means.

Typical machine vision-based techniques allowing for a constant observation of a driver work often in the following manner. The first stage is face detection followed by facial features extraction [22]. Such regions-of-interest are then analysed in order to collect relevant spatial and temporal characteristics which are subjected to inference mechanism. Face and face features detection problems are considered solved under controlled conditions [10, 31], yet when we deal with severe lighting, there are still many difficulties to overcome.

It is evident, that the analysis of the visible band image of a face recorded in the unfavourable illumination leads to the high error rate or it can be completely impossible. On the other hand, under the same environmental conditions, using thermal imaging, we are able to detect eyes blinking and yawning. Hence, we propose a method to detect eyes and mouth state in video sequences captured in thermal spectrum. Although the detection and tracking of facial landmarks can be performed with almost 100% accuracy, it should be remembered, that they are oriented at visible band images. Their accuracy for other modes, e.g. thermal images or depth maps, is not often explored. It is caused by unpopular and expensive thermal acquisition devices. However, it may change in future.

The authors of [17] presented a method of detecting yawning in thermal images for estimating driver's fatigue level. They focus on detecting thermal anomalies in the image area where a mouth is located. This approach may be sensitive to an unexpected phenomenon, unforeseen while determining their parameters empirically. In our approach we detect mouth state based on visual cues only, assuming that the appearance of the lips changes during yawning. Another exemplary system presented in [24] uses OpenCV face and eye detectors supported with the simple feature extractor based on the two dimensional Discrete Fourier Transform (DFT) to represent eyes regions. Similarly, the fatigue of the driver determined through the duration of the eyes' blinks is presented in [8]. It operates in the visible and near infra-red (NIR) spectra allowing to analyse drivers state in the night conditions and poor visibility. A more complex, multimodal platform to identify driver fatigue and interference detection is presented in [7]. It captures audio and video data, depth maps, heart rate, steering wheel and pedals positions. The experimental results show that the authors are able to detect fatigue with 98.4% accuracy. There are solutions based on mobile devices, especially smartphones and tablets, or based on dedicated hardware [14, 18, 34]. In [1] the authors recognize the act of yawning using a simple webcam. In [12] the

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

authors proposed a dynamic fatigue detection model based on Hidden Markov Model (HMM). This model can estimate driver fatigue in a probabilistic way using various physiological and contextual information. In a subsequent work [3] authors monitor information about the eyes and mouth of the driver. Then, this information is transmitted to the Fuzzy Expert System, which classifies the true state of the driver. The system has been tested using real data from various sequences recorded during the day and at night for users belonging to different races and genders. The authors claim that their system gives an average recognition accuracy of fatigue close to 100% for the tested video sequences.

The analysis shows that many of current works are focused on the problem of recognizing driver's fatigue, yet there is no common methodology of acquisition of signals (from various sources) used to evaluate vehicle operator physical condition and fatigue level. Moreover, most of works focus on single feature, not taking into consideration joint observations. Even though, if joint features are used (e.g. [27]), the analysis is performed on visible-light-only images.

On the other hand, to achieve the most accurate results, researchers use additional data sources such as EEG, ECG, heart rate, vehicle behavior on the road, etc. Unfortunately, in real conditions, obtaining this type of data is difficult or even impossible. Therefore, in their research, the authors focus on non-invasive methods of image analysis of various spectra [15, 28, 30].

2 Method description

2.1 Assumptions

Capturing image in visible-band light is the most straightforward and widespread method of visual data acquisition. The sensors of photo cameras are rather cheap and their performance can be high, in terms of sensitivity, dynamic range and spatial resolution. Unfortunately, their parameters are preserved only in good and stable lighting conditions. It should be remembered that car's cabin is often illuminated by directional light, coming from the windows (sun, street and lamps of other cars). What is more, additional (stable) lighting of driver's face during driving is impossible, since it could disturb his/her functioning. The natural way of solving this dilemma is using other capturing device, working in different lighting spectra, e.g. near infrared (NIR with wavelength of 0.75–1.4μm) or thermal (also known as long-wavelength infrared - LWIR with wavelength of 8–15μm). Since NIR is associated with so called reflective infrared, it requires an illumination with infrared illuminator. Such a prolonged illumination may be hazardous to the driver's health [4]. Therefore, the LWIR spectrum has been selected, since it is free of the above mentioned weak points [17]. Thermal sensor captures drivers's facial image in a completely passive manner and it does not depend on the lighting conditions, which is important when dealing with an observation of a driver in uncontrolled environment.

Using the same methodology, as in case of visible-band video, certain facial areas in the thermal portraits can be detected and extracted using specially

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

trained detectors based on hand-crafted features, e.g. Haar-like features [13], Histogram of Oriented Gradients [13] and Local Binary Patterns [34]. The detectors are often trained by means of some variant of AdaBoost approach [6, 14]. It should be also noted that recently proposed deep-learning applications [26] require significant computing power to operate in near-real-time.

2.2 General overview

The algorithm consists of six main modules: (i) face detection and tracking, (ii) eyes detection and tracking, (iii) eyes state analysis, (iv) mouth detection and tracking, (v) mouth state analysis, and (vi) data integration, leading to the estimation of driver state detection. It works in a loop iterated over the frames from the video stream (see Fig. 1).

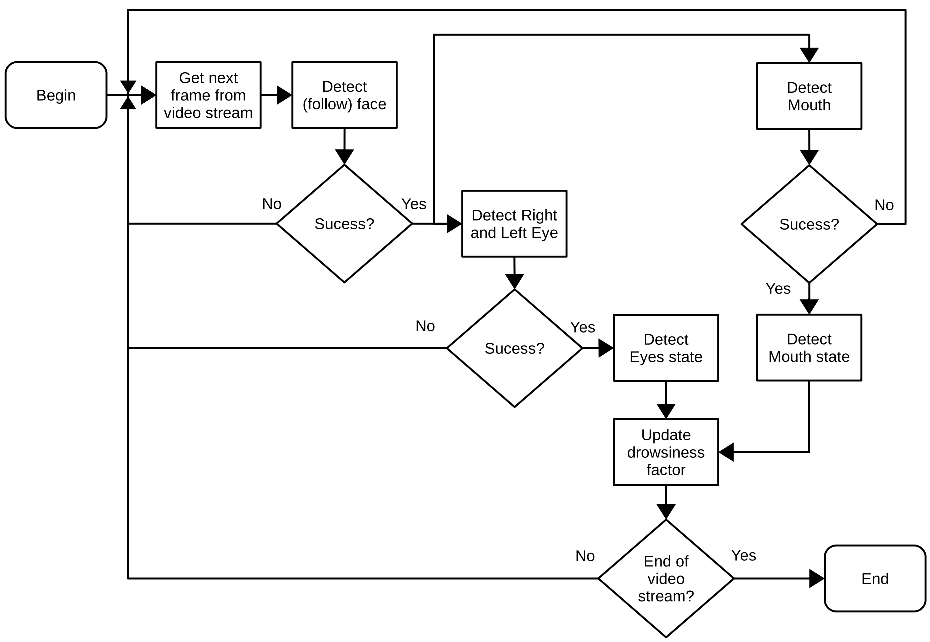

Fig. 1. Algorithm of drowsiness estimation by means of eyes and mouth state analysis.

2.3 Region detectors

The input video stream is processed in frame-by-frame manner. Each frame is a subject of independent face, eyes and mouth detection. Firstly, a pretrained Viola-Jones detector [10] is used to detect faces. A successful detection triggers simple face tracker, that assumes only small movement of the head in consecutive

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

frames and approximates position between successful detections. The previous research [10, 11, 25] showed, that it is possible to perform an efficient and precise face detection in images taken in non-visible bands. Previous experiments involving thermal images [10] showed also, that although traditional Viola-Jones detector using hand-crafted features is not so strong as many recently proposed deep-learning approaches, it requires less computations and is capable of working in real-time.

Detected face's boundaries are the subject of parallel eyes and mouth detectors. Actually, there are three separate detectors, one for each eye and for mouth, all based on Viola-Jones approach, trained on a set of over 1700 eyes and 1450 mouth samples extracted from benchmark video streams captured in our simulated cabin [20]. Since the detection may not always precisely estimate the position of eyes and mouth, we introduced a tracker that is based on position approximation [11], assuming that under regular driving conditions eyes and mouth positions should not change significantly across a small number of neighbouring frames.

Taking into consideration the above mentioned assumptions, the resulting coordinates of the face's, eyes' and mouth's bounding boxes are calculated over the averaged 10 past detections. Final confidence level is normalized to the range $\langle 0, 1 \rangle$. Some exemplary detection results are presented in Fig. 2. As it can be seen, face orientation does not influence the detection performance.

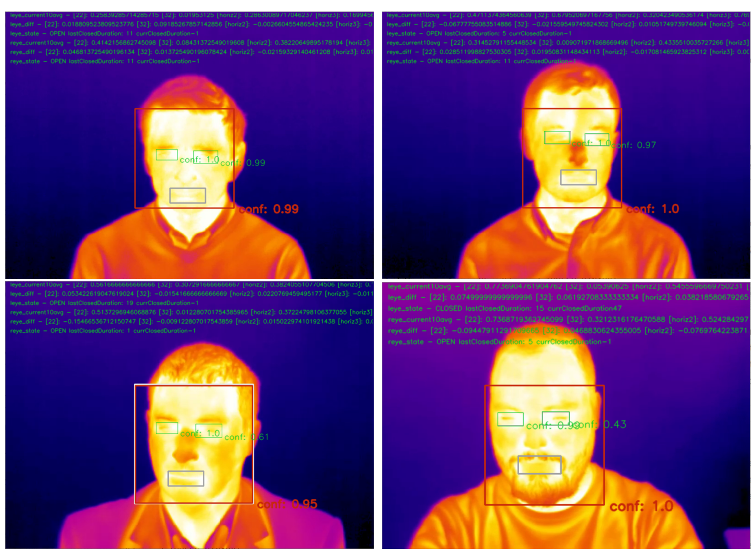

Fig. 2. Exemplary results of face tracking joint with eyes and mouth detection.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

2.4 Eyes and mouth state estimation

Extracted eyes and mouth regions are then predicted as open or closed. Both stages work in the similar manner, hence they are described as a single universal procedure. The classification is performed in the following steps (for each eye and mouth separately):

1. Extract eye (mouth) region from detected face region;
2. Resample the image to a fixed rectangle of 100×50 pixels;
3. Filter the image with Gabor filter bank (30 sets of parameters resulting in 30 output images);
4. Calculate energy and standard deviation for each resulting image (resulting in 60 values);
5. Concatenate above coefficients into a singe feature vector;
6. Perform the classification.

Gabor filtering [2] is performed with kernel size equal to 20×10, standard deviation of the Gaussian envelope equal to 2.5, spatial aspect ratio equal to 5.0 and phase offset equal to $3\pi/2$. By altering the orientation angle of the normal to the parallel stripes of a Gabor function in the range $\langle 0, 5\pi/6 \rangle$ with a $\pi/6$ step and wavelength of the sinusoidal factor equal to $\{1, 2, 4, 8, 16\}$ we get 30 output images. These parameters are in line with the literature [5] and give the possibility to obtain a compact textural representation. For every filtering result we calculate energy (normalized by the image's dimensions) and standard deviation. Resulting feature vectors are then taken as input for the binary classifier.

Exemplary results of filtering for eye region are presented in Fig. 3. The left part of the image shows closed eye, while the right one - open eye, respectively. Similarly, the results of filtering for mouth region are presented in Fig. 4, where the left part of the image is devoted to the closed mouth, while the right one to the open mouth, respectively.

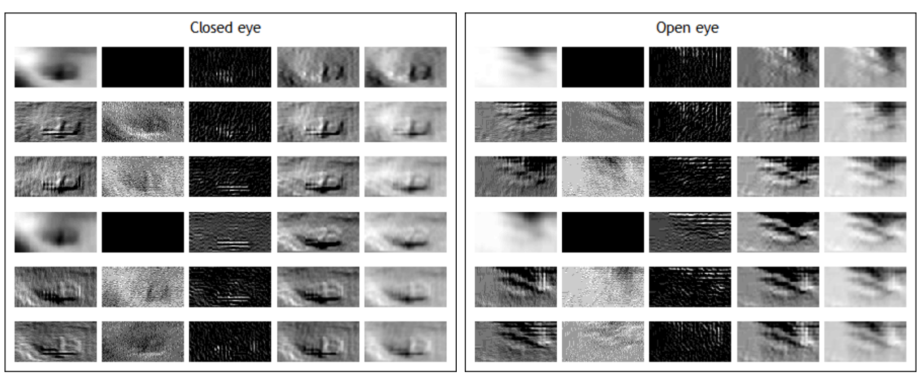

Fig. 3. Selected images of eyes regions after Gabor filtering.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

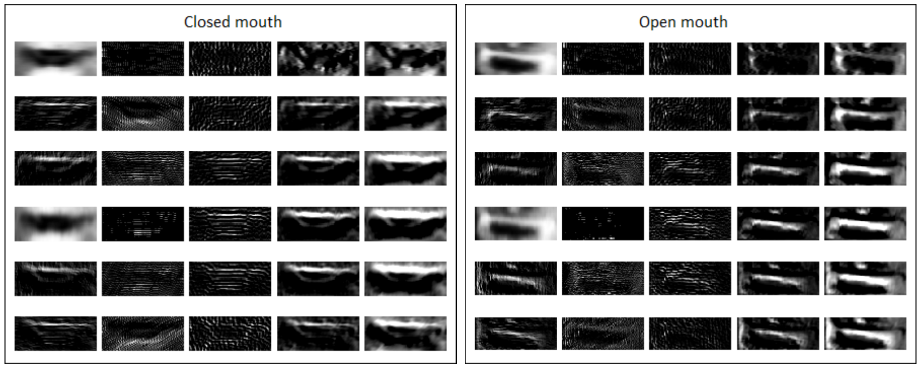

Fig. 4. Selected images of mouth regions after Gabor filtering.

2.5 Drowsiness factor estimation

We estimate fatigue state on a basis of eyelids closing time and mouth opening time. We adopted PERCLOS indicator (PERcentage of eye CLOSure) [16] in case of eye's analysis. Despite the more frequent opinion about PRECLOS cons, the method is still popular and the most accurate way to measure alertness bases only on visual data. More complex approaches require to use of inconvenient devices like EEG, EOG, heart rate monitors, etc. [23, 30]. This indicator is represented as a proportion of time for which eyes are more than 80% closed (percentage of eye closure). It is usually calculated accumulatively over a predefined interval. As drowsiness often occurs after fatigue, yawning detection is an important factor to take into account because it is a strong signal that the driver can be affected by drowsiness in a short period of time. We estimate it by means of mouth opening time (we call it PEROPEN - PERcentage of mouth OPENing), as the number of frames where mouth state is predicted as closed, to the length of the examined time vector. The longer the time window is, the smoother the PERCLOS and PEROPEN functions are.

3 Experiments

3.1 Dataset

The data were gathered in Computer Vision Laboratory, Faculty of Computer Science and Information Technology, West Pomeranian University of Technology, using a proprietary simulation stand (see Fig. 5). The acquisition protocol of the benchmark data has been presented in [21]. All video materials have been recorded using FLIR SC325 camera working in LWIR band, equipped with 16-bit sensor of 320×240 and a lens of 25×18.8 degree FOV.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

Fig. 5. Experimental stand used for capturing video sequences

3.2 Evaluation protocol

All algorithms have been implemented in the Python environment together with OpenCV, and SciKit-learn libraries. Original database includes records of 50 persons with different characteristics (women, men, people with and without beards, with and without glasses, young ones and older). We selected records of four persons of different physiognomy and manually annotated 10800 ground truth frames [21]. The set contained the following number of samples: left eye – 5558 (opened), 2414 (closed) and right eye – 8192 (opened), 4013 (closed). The respective numbers for mouth regions – 281 frames with open mouth, and 1170 with a closed mouth.

Initially, we experimented with typical binary classifiers on features extracted from eyes and mouth regions, independently. This part of the experiment was performed using Weka software. The hyperparameters for all classifiers was chosen according to typical and default settings. The mean values for 10-fold cross-validation for True Positive and False Positive rates are presented in Tab. 1. As a compromise between accuracy and computational overhead, we selected kNN ($k = 1$) to be implemented in further software.

The aim of both experiments was to verify the ability to identify images containing open and closed eyes/mouth regions in connection with face and eyes/mouth detection stages. The influence of the confidence level (responsible for the detection accuracy) on the eyes/mouth state detection was also investigated. It led to the observation that if we increase the confidence level (resulting in more eyes' candidates and more mouth's candidates being rejected), the classifier performs quite well. At the same time, if the confidence level drops, the overall accuracy also goes down.

3.3 Results

In comparison to the manually annotated video, our algorithm has an average accuracy near 70% for eyes and 87% for mouth state detection, respectively.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

Table 1. The results of the experiments on the classification of eyes and mouth state (the best results are highlighted).

Classifier	True positive rate Mouth	True positive rate Eyes	False positive rate Mouth	False positive rate Eyes
1NN	0.989	0.962	0.035	0.053
Kstar	0.987	0.962	0.044	0.053
Random Forest	0.992	0.947	0.029	0.089
Bagging	0.985	0.909	0.044	0.155
MultiLayerPerceptron	0.989	0.889	0.027	0.172
j48 (C4.5 decision tree)	0.980	0.887	0.040	0.153
Random Tree	0.986	0.886	0.033	0.159
Classification via Regresion	0.988	0.876	0.025	0.193
REPTree	0.979	0.855	0.059	0.215
SimpleLogistic	0.989	0.748	0.032	0.435
SVM with SMO	0.989	0.728	0.032	0.586
NaiveBayes	0.975	0.637	0.052	0.283

It is important that most of the blinking eyes are detected, sometimes with a small delay, which is caused by a proposed buffer analysis. Likewise, for yawning detection algorithm we observe similar small delay, but comparing to the average blinking time, this delay is not crucial. In Fig. 6 the impact of buffer size on the detection accuracy is shown. For every single frame classification, the output value of analysis was the majority of states in the buffer. Using the buffer solves the problem of single frame misclassification, but in the long term it has a small negative impact on overall accuracy level (0.2% - 0.6%). The accuracy results were calculated as a weighted average of accuracies for both states according to the number of frames.

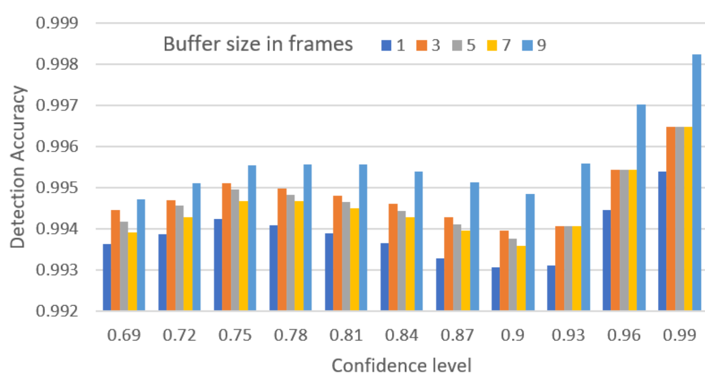

Fig. 6. The influence of mouth state buffer size, confidence level on detection accuracy

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

The accuracy changes following the detectors' confidence. As it was anticipated, the confidence influences the detector performance. If the confidence is lower, then the total number of detected eye candidates is higher. The lower the detector confidence, the eyes state classifier's accuracy is also lower (see Fig.7) since detected eyes are of poorer quality. Hence, if the eyes are detected with higher confidence, the eyes state classifier performs also with higher accuracy. The characteristic shape of accuracy curve for mouth state detection is caused by a significant decrease in the number of frames presenting open state at the classification stage (in the worst case 0.1% of all collected samples).

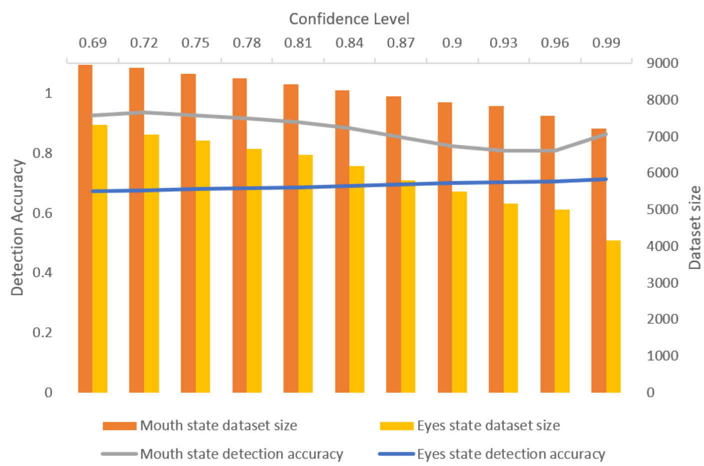

Fig. 7. The influence of dataset size (based on confidence level) on detection accuracy.

In Fig. 8 a visualization of mouth state detection accuracy is shown for a test sequence (frame numbers are on horizontal axis). The upper part of the figure presents the close state, and the bottom part shows the open mouth state. Blue blocks present ground true (annotated), while orange blocks present detected state. Visible three gaps in the further part of the video are caused by mouth occlusion (covering mouth with hand while yawning). The mouth was not detected there (only approximated by the tracker) and low confidence factor did not allow to make the prediction. An analogous visualization for eyes state detection is in Fig. 9.

In Fig. 10 the PERCLOS and PEROPEN functions calculated for the test sequence are presented. Given the short length of the test recording, a vector length of 800 frames was assumed. In case of a prolonged time of observation, longer buffers may be used. The analysis of above coefficients is based on the threshold which is responsible for estimating the drowsiness factor. By thresholding their values we can find the moments in time when the fatigue level increases and the drowsiness occurs. For both PERCLOS and PEROPEN, it is advisable

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

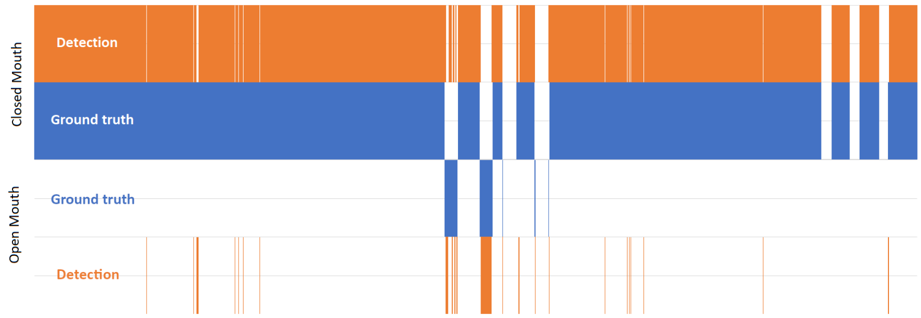

Fig. 8. Detection accuracy in time visualisation for mouth state detection.

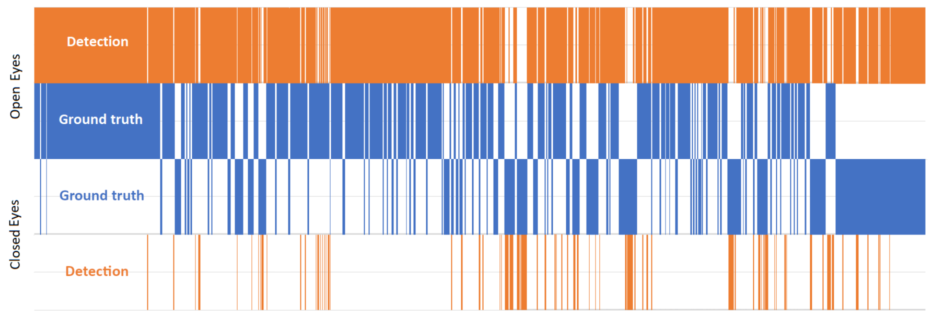

Fig. 9. Detection accuracy in time visualisation for eyes state detection.

to set it to 0.15. As it can be seen, from frame nr 4500, the sequence of two yawns and more frequent eyes blinking begins, which may indicate actual drowsiness.

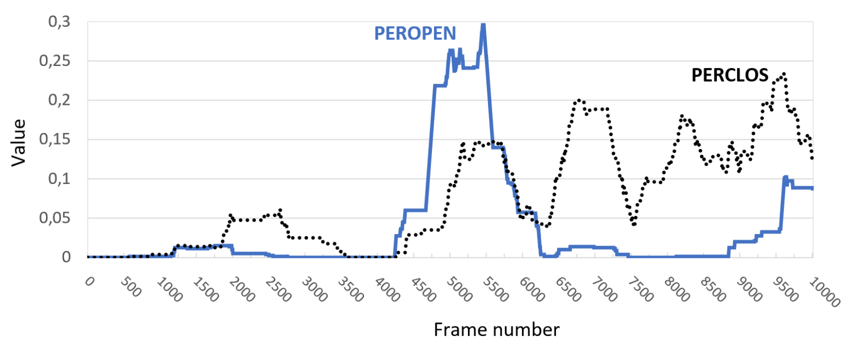

Fig. 10. PERCLOS and PEROPEN indicators for eyes and mouth states, respectively.

In order to evaluate the possibility to implement the algorithm in the mobile environment, we performed the tests involving three hardware platforms:

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

PC-based desktop (as a baseline) and two single-board computers (Raspberry PI 4 and NVidia Jetson AGX). It should be remembered that the algorithm was implemented in Python, not being the most optimal solution for end-user applications. Table 2 contains processing times of detection algorithm for the test sequence. As it can be seen, prototype implementation is not dedicated to single-board computers. On the other hand, for yawning detection only, the processing time is acceptable results. Unfortunately, for blinking detection, some optimizations should be performed to allow for real-time operation.

Table 2. Processing times on different hardware platforms

Platform/Device	Time [s]	FPS
PC (Intel Xeon E5645 @2.4GHz)	2665.59	4.06
nVidia Jetson AGX Xavier	3591.26	3.01
Raspberry pi4	6265.82	1.73

4 Conclusions

In the paper, we showed an algorithm of eyes and mouth state estimation based on thermal image analysis that may by used to detect driver's drowsiness. It consists of face, eyes and mouth detection and eyes and mouth state classification. It uses Haar-like features and Viola-Jones detector, while eyes and mouth states are classified using Gabor-filtered images with k-Nearest Neighbour classifier.

Application of thermal images here is a new approach, making the results resistant to many problems caused by visible spectrum imaging. A new contribution is also the introduction of the confidence coefficient that can be used to tune final system reliability. It should be remembered, the analysis of thermal images also has some limitations, e.g. the problem of eyes occlusion by thick transparent materials (e.g. glasses). In such case, we are forced to use mouth-only classifier.

The experiments showed that it is possible to detect eyes and mouth state in uncontrolled lighting conditions with significant accuracy. The results are competitive with the other proposals [7, 8]. From the practical point of view, when fatigue is detected, the Advanced Driver Assistance System can stimulate the driver e.g. with acoustic or visual signals. What is more, in critical situations, after detecting severe fatigue or sleep, such system may even stop the vehicle.

In order to create a final solution, resistant to the problems presented above, future works in this area will include the integration of data from other imaging modalities, e.g. depth maps. It is also planned to analyse more types of driver's behaviour, e.g. head tilting, changing the focal point of sight or covering the mouth when yawning. These actions could be successfully recognized with help of current deep-learning based detectors, like CNNs or LSTMs. Since those approaches require significantly higher computing power, they were not considered at the present stage of development.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

References

1. Alioua, N., Amine, A., Rziza, M.: Driver's fatigue detection based on yawning extraction. Int. J. of Vehicular Technology, vol. 2014, Article ID 678786, 7 pages (2014)
2. Andrysiak, T., Choras, M.: Image retrieval based on hierarchical Gabor filters, International Journal of Applied Mathematics and Computer Science vol. 15, no.4, 471–480 (2005)
3. Azim, T., Jaffar, M. A., Mirza, A. M.: Fully automated real time fatigue detection of drivers through fuzzy expert systems. Applied Soft Computing 18, 25–38 (2014)
4. Berglund, B., Rossi, G. B., Townsend, J. T., Pendrill, L. R.: Measurement With Persons: Theory, Methods, and Implementation Areas, Psychology Press, 422 p. (2013)
5. Bianconi, F., Fernandez, A., Evaluation of the effects of Gabor filter parameters on texture classification, Pattern Recognition, vol. 40, Iss. 12, 3325–3335 (2007)
6. Burduk, R.: The AdaBoost Algorithm with the Imprecision Determine the Weights of the Observations. Intelligent Information and Database Systems, Pt II, LNCS, Vol. 8398, 110–116 (2014)
7. Craye, C., Rashwan, A., Kamel, M. S., Karray, F.: A multi-modal driver fatigue and distraction assessment system. Int. J. of Intel. Transp. Syst. Res. 14(3), 173–194 (2016)
8. Cyganek, B., Gruszczynski, S.: Hybrid computer vision system for drivers' eye recognition and fatigue monitoring. Neurocomputing 126, 78–94 (2014)
9. Daza, I.G., Bergasa, L.M., Bronte, S., Yebes, J.J., Almazán, J., Arroyo, R.: Fusion of Optimized Indicators from Advanced Driver Assistance Systems (ADAS) for Driver Drowsiness Detection. Sensors, 14, 1106–1131 (2014)
10. Forczmański, P.: Performance Evaluation of Selected Thermal Imaging-Based Human Face Detectors. 10th Int.Conf. on Comp. Recog. Sys. CORES 2017. Adv. in Intell. Syst. and Comp., vol 578, 170–181 (2018)
11. Forczmański, P., Kutelski, K.: Driver Drowsiness Estimation by Means of Face Depth Map Analysis. In: Advances in Soft and Hard Computing. ACS 2018. Advances in Intelligent Systems and Computing, vol 889, 396–407 (2019)
12. Fu, R., Wang, H., Zhao, W.: Dynamic driver fatigue detection using hidden Markov model in real driving condition. Exp. Syst. with Appl. 63, 397–411 (2016)
13. Hussien, M. N., Lye, M., Fauzi, M. F. A., Seong, T. C., Mansor, S.: Comparative analysis of eyes detection on face thermal images, 2017 IEEE Int. Conf. on Signal and Image Processing Applications (ICSIPA), Kuching, 385–389 (2017)
14. Jo, J., Lee, S. J., Park, K. R., Kim, I. J., Kim, J.: Detecting driver drowsiness using feature-level fusion and user-specific classification. Exp. Syst. with Appl. 41(4), 1139–1152 (2014)
15. Josephin, J., Lakshmi, C., James, S.: A review on the measures and techniques adapted for the detection of driver drowsiness. IOP Conference Series: Materials Science and Engineering. 993. 012101. 10.1088/1757-899X/993/1/012101. (2020)
16. Knipling, R. R., Wierwille, W. W.: Vehicle-based drowsy driver detection: Current status and future prospects. In Moving Toward Deployment. Proceedings of the IVHS America Annual Meeting. 2 Volumes, Volume 1 245–256 (1994)
17. Knapik, M., Cyganek, B.: Driver's fatigue recognition based on yawn detection in thermal images. Neurocomputing 338, 274–292 (2019)
18. Kong, W., Zhou, L., Wang, Y., Zhang, J., Liu, J., Gao, S.: A system of driving fatigue detection based on machine vision and its application on smart device. J. of Sensors, Article ID 548602 (2015)

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12

19. Krishnasree, V., Balaji, N., Rao, P. S.: A Real Time Improved Driver Fatigue Monitoring System. WSEAS Trans. on Signal Processing 10, 146–155 (2014)
20. Małecki, K., Forczmański, P., Nowosielski, A., Smoliński A., Ozga, D.: A New Benchmark Collection for Driver Fatigue Research Based on Thermal, Depth Map and Visible Light Imagery. Progress in Computer Recognition Systems. CORES 2019. Adv. in Intell. Syst. and Comp., vol 977, 295–304 (2020)
21. Małecki, K., Nowosielski, A., Forczmański, P.: Multispectral Data Acquisition in the Assessment of Driver's Fatigue, 17th Int. Conf. on Transport Systems Telematics (TST), Communications in Computer and Information Science, vol. 715, 320–332 (2017)
22. Mitas, A., Czapla, Z., Bugdol, M., Rygula, A.: Registration and evaluation of biometric parameters of the driver to improve road safety. Scientific Papers of Transport, Siles. Univ. of Technology, 71–79 (2010)
23. Nissimagoudar, P., Nandi, A. V., Gireesha., H.M.: A Feature Extraction and Selection Method for EEG Based Driver Alert/Drowsy State Detection. Proceedings of the 11th Int. Conf. on Soft Computing and Pattern Recognition (SoCPaR 2019). 297–306 (2021)
24. Nowosielski, A.: Vision-based solutions for driver assistance. J. of Theor. and Appl. Comp. Sc. 8(4), 35–44 (2014)
25. Nowosielski, A., Forczmański, P.: Touchless typing with head movements captured in thermal spectrum, Pattern Analysis and Applications, vol. 22, Iss. 3, 841–855 (2018)
26. Poster, D., Hu, S., Nasrabadi, N.M., Riggan, B.S.: An Examination of Deep-Learning Based Landmark Detection Methods on Thermal Face Imagery, 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 980–987, (2019)
27. Sacco, M., Farrugia, R. A.: Driver fatigue monitoring system using Support Vector Machines, 2012 5th Int. Symposium on Communications, Control and Signal Processing, Rome, 1-5 (2012)
28. Satish, K., Lalitesh, A., Bhargavi, K., Prem, Sishir, M. Anjali, T.: Driver Drowsiness Detection. 2020 Int. Conf. on Communication and Signal Processing (ICCSP), 0380–0384. (2020)
29. Smolensky, M. H., Di Milia, L., Ohayon, M. M., Philip, P.: Sleep Disorders, Medical Conditions, and Road Accident Risk. Accident Analysis and Prevention 43(2), 533–548 (2011)
30. Trutschel, U., Sirois, B., Sommer, D., Golz, M,. Edwards, D.: PERCLOS: An Alertness Measure of the Past. Proceedings of the Sixth Int. Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design. 172–179 (2017)
31. Viola, P., Jones M. J.: Robust Real-Time Face Detection. Int. J. of Comp. Vis. 57(2), 137–154 (2004)
32. Virginia Tech Transportation Institute. Day or Night, Driving while Tired a Leading Cause of Accidents (2013) `http://www.vtnews.vt.edu/articles/2013/04/041513-vtti-fatigue.html`
33. Weller, G., Schlag, B.: Road user behavior model. Deliverable D8 project RIPCORD-ISERET, 6 Framework Programme of the European Union (2007) `http://ripcord.bast.de`
34. Zhang, Y., Hua, C.: Driver fatigue recognition based on facial expression analysis using local binary patterns. Optik – Int. J. for Light and Electron Optics 126(23), 4501-4505 (2015)

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77977-1_12