



Statistical Relationship among Driver's Drowsiness, Eye State and Head Posture

Research Article

Lam Thanh Hien¹, Thanh-Lam Nguyen² and Do Nang Toan³

¹Office of Academic Affairs, Lac Hong University, Vietnam

²Office of Scientific Research, Lac Hong University, Vietnam

³Graduate University of Science and Technology, Vietnam National University, Vietnam

*Corresponding author: green4rest.vn@gmail.com

Abstract. Many serious accidents in road traffic are resulted from driver's drowsiness, leading to special efforts in improving traffic safety by searching for optimal models to accurately detect and alert driver's drowsiness. Thus, numerous scholars worldwide have paid special interest in proposing a great number of detection methods, among which visual feature-based approaches, such as eye state, head movement, yawning, facial expressions, etc., have been most preferred as they are non-intrusive and effectively detect drowsiness. However, the current literature fails to show the statistical relationships among the driver's drowsiness, eye state and head posture. Thus, the statistical linear regression and binary logistic regression models found in this paper fill the existing gap; especially, the eye state should be determined by simultaneously monitoring the eye states of both eyes and it has greater impact on the detection ability than that of head posture. More importantly, the interactive combination of eye state and head posture provides better detection ability. Our proposed logistic regression model can correctly detect 99.1% of the total investigated observations in a practical experiment study.

Keywords. Driver's drowsiness; Drowsiness detection; Eye state; Head posture; Statistical relationships; Linear regression; Logistic regression

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1. Introduction

Many serious accidents in road traffic are resulted from driver's drowsiness which usually occurs when a driver fails to have enough sleep or enough rest for/after a long trip, leading

to a decrease in his/her observation and reaction ability [13, 14]. As a matter of fact, drivers feel fatigued if they sit still for a long time due to the vibration, noise, and shaking of the vehicles. If fatigued, they should take a proper rest before continuing their trips to avoid falling into drowsiness which leads to distraction and unconscious state or even seriously loses their control of the vehicle awhile. Losing the control of the vehicle just only a few seconds may cause a terrible disaster as they fail to effectively reflex to avoid obstacles and/or other vehicles [13, 14]. Therefore, searching for optimal models to accurately detect and alert driver's drowsiness has been an interesting research topic that attracts special attention of numerous scholars [1, 4, 5, 7–11, 15–17, 19–22, 24–36, 38–44, 46–49]. Jo *et al.* [19] and Dong *et al.* [8] classified the existing approaches into three categories, including (i) driving behavior-based approaches; (ii) physiological feature-based approaches; and (iii) visual feature-based approaches. Among these categories, visual feature-based approaches have been most preferred as they are non-intrusive by providing tracking information obtained from a camera mounted on vehicle [17].

Specifically, there have also been a great number of detection methods such as eye state, head movement, yawning, facial expressions, etc., proposed in the third category [17]. Methods using eye state to measure driver drowsiness, investigated by Eriksson and Papanikotopoulos [9], Parmar [32], Bergasa *et al.* [4], Orazio *et al.* [30], Wu and Trivedi [47], Adachi *et al.* [1], Li [25], Wang *et al.* [44], Yunq *et al.* [49], Bhowmick and Kumar [5], Ince and Yang [15], Noguchi *et al.* [29], Sukno *et al.* [38], Flores and Armingol [11], Jo *et al.* [20], Tsuchida *et al.* [41], Jo *et al.* [19], Panning *et al.* [31], Kurylyak *et al.* [24], Minkov *et al.* [27], and Uliyar and Ukil [42], generally calculate values such as eye closure duration (ECD), the *frequency of eye closure* (FEC) [30], and *percentage of eye closure* (PERCLOS) [45]; and they have already shown superior accuracy in detecting drowsiness [43]. Meanwhile, methods using head movement to measure drowsiness by estimating head posture can be effectively used to infer attention focus of humans [2, 6, 14, 21, 28, 37].

However, the current literature fails to show the statistical relationships among the driver's drowsiness, eye state and head posture. This paper aims at filling the gap with an appropriate statistical model for the relationships that can be used to identify the probability of becoming drowsy in consideration of eye state and head posture. To achieve that, multiple linear regression with *ordinary least square* (OLS) method and binary logistic regression are suggested.

The rest of this paper is organized as the following. Section 2 presents an overview of some prominent approaches in classifying eye state and head posture while the fundamental issues of the multiple linear regression and logistic regression models are discussed in Section 3. Empirical data collection and analyses make up Section 4. And brief concluding remarks are finally presented in the last section.

2. Literature Review

2.1 Methods of Classifying Eye State

Jo *et al.* [17] gave a brief review of the existing approaches in classifying eye states as open or close. The methods proposed by Eriksson and Papanikotopoulos [9], Parmar [32], Bergasa *et al.* [4], Orazio *et al.* [30], Wu and Trivedi [47], Li [25], Flores and Armingol [11], Jo *et al.* [20], Jo *et al.* [19], Panning *et al.* [31], Kurylyak *et al.* [24], Minkov *et al.* [27], and Uliyar

and Ukil [42] basically work with different extraction algorithm to effectively extract texture features of eyes to finally classify eye state; thus, they are grouped as “texture-based methods”. For examples, Eriksson and Papanikotopoulos [9] and Parmar [32] suggested using histogram plots of local eye image; Wu and Trivedi [47] proposed Tensor principal component analysis (PCA); or Gabor response waves by Li [25] and Flores and Armingol [11]; frame differencing by Bergasa *et al.* [4] and Kurylyak *et al.* [24]; edge of local eye image by Orazio *et al.* [30] and Jo *et al.* [20].

Notably, Jo *et al.* [19] proposed combining appearance features, extracted from *principal component analysis* (PCA) and *linear discriminant analysis* (LDA), and statistical features, derived from the sparseness and kurtosis of the histogram from the eye-edge image. Or, Minkov *et al.* [27] suggested using some typical characteristics such as raw-image intensities, the magnitude of the responses of Gabor filters, the pyramid histogram of oriented gradients (PHOGs), and optical flow as the inputs for the *Gaussian radial basis function* (GRBF) kernels in a support vector machine (SVM) while Uliyar and Ukil [42] proposed calculating *local binary pattern* (LBP) histogram features from the input eye image before using a *canonical correlation analysis* (CCA), which was claimed to improve the classification accuracy about 10-12% compared to those using normalized intensity-based features.

Alternatively, Adachi *et al.* [1] proposed using two separate searching windows to detect eyelids by measuring their distances in both eyes while Wang *et al.* [44], Sukno *et al.* [38] and Noguchi *et al.* [29] used an *active shape model* (ASM) to extract eye contours before similarly measuring the eyelid distances in both eyes. Or, Ince and Yang [15] and Tsuchida *et al.* [41] proposed measuring the distance between upper and lower eyelids to classify eye state. Thus, these methods are grouped as “shape-based methods” [17].

Or, Bhowmick and Kumar [5] and Yunq *et al.* [49] proposed taking the advantages of these two groups to have a more robust classification of eye state by using a nonlinear SVM trained with both texture-based features and shape-based features extracted from the input eye image. The classification approach proposed by Hien *et al.* [13] was claimed to run in real-time speed with high accuracy in detecting eye state measured in seconds or frames. Moreover, their approach is found also very simple; thus, promising a high applicability in practice. Therefore, this paper employs Hien *et al.* [13]’s approach in classifying eye states as inputs for our statistical model.

2.2 Methods of Classifying Head Posture

Besides the prominent eye state approaches in detecting driver’s drowsiness as discussed above, head posture is also an interesting research topic in the field, attracting special attention of Kawato and Ohya [21], Murphy-Chutorian *et al.* [28], Smith *et al.* [37], Benfold and Reid [2], Chamveha *et al.* [6], Hien *et al.* [14]. Literally, head posture can be a good indicator of drowsiness [3] because drowsy driver’s head posture is greatly different from that of alert one. Ji and Yang [18] pointed that alert drivers normally look straight ahead whereas drowsy ones frequently look in other directions for a period of time. Kito *et al.* [23] proposed measuring head postures with a gyroscope during driving activity. However, they only investigated the head postures of drivers at specific intervals rather than the effect of drowsiness on head postures.

Thus, Berg [3] claimed that the relationship between drowsiness and head posture over time is rarely investigated.

Moreover, Hien *et al.* [14] argued that a drowsy person is normally observed with head bend posture or head in slanting state which makes the detection of drowsy driver more difficult because his/her face fails to be in-line with the equipped camera. In addition, the shaking of vehicle or the driver's winking even makes the problem much more complicated. However, head bend posture can also be inferred as a signal of drowsiness. Therefore, they successfully proposed an advanced model based on the well-known facial normal approach. The model was claimed to provide an accuracy level of 96.56% of investigated cases. Due to the excellent performance of their approach, it is employed in this paper to collect necessary data of head postures (as normal or nodding) as inputs for our statistical model.

3. Primaries about Linear Regression and Logistic Regression

3.1 Multiple Linear Regression

Regression analysis is preferably used to uncover the statistical relationships between independent variables (causal variables) and a dependent variable (influenced ones). The estimated relationships are typically evaluated with a so-called "statistical significance" which is referred as the degree of confidence that the true relationship is close to the estimated one [12]. Conventionally, a multiple linear regression usually comes in the following general form:

$$y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n,$$

where y denotes dependent variable; x_1, x_2, \dots, x_n denote independent variables; a_1, a_2, \dots, a_n are called "Regression coefficients".

The statistical relationships between the dependent variable and independent ones are interpreted from the regression coefficients which represent the quantitative effect of each independent variable on the estimated change of the dependent one while other independent variables are kept unchanged. Regression coefficient is effectively obtained with *least squares* (LS) methods. Among several existing variations, *ordinary least squares* (OLS) method is preferably used due to its simple computation.

OLS is useful in estimating the values of the coefficients such that providing the minimum sum of the squares between the observed and modeled values of the dependent variable. Particularly, assume that we have m observations and let y_i and \hat{y}_i be respectively the observed and modeled values of y at the entry i th; then, the residual of this entry is defined as:

$$\varepsilon_i = y_i - \hat{y}_i = y_i - a_0 - a_1x_{1i} - \cdots - a_nx_{ni} \quad (i = \overline{1, m}).$$

The OLS method is expressed as: $\sum_{i=1}^m \varepsilon_i^2 \rightarrow \min.$

Nowadays, solving such objective in linear programming is really easy in several computer softwares. Hence, the parameters a_0, a_1, \dots, a_n in the regression models are also easily obtained. However, the validity of the model and each coefficient should be carefully tested. Traditionally, obtained significance level, abbreviated as "Sig." or "*p-value*" in computational programs, is

used for the tests and compared to a given significance level (α) which is actually the probability that a null hypothesis is rejected when it is in fact true and should not have been rejected. α is usually set at 5%. Once the obtained significance level of a model or a variable is not greater than α , the model or the variable is respectively said to be statistically significant. A significant model is well believed to fit to actual data set in the real phenomena; and an insignificant variable should be dropped out from the regression model [12].

Literally, the goodness-of-fit of a linear model can be judged with some measures, such as the *determination coefficient* (R^2), *root mean square error* (RMSE), *mean absolute percentage error* (MAPE), etc. Among them, *adjusted determination coefficient* (\bar{R}^2) is commonly used for multiple linear regression. It is determined by:

$$\bar{R}^2 = \left[1 - \frac{\sum_{i=1}^m (y_i - \hat{y}_i)^2}{\sum_{i=1}^m (y_i - \bar{y}_i)^2} \right] \times \frac{m-1}{m-n-1}.$$

3.2 Binary Logistic Regression

When dealing with a dichotomous categorical dependent variable, we count the frequency of a given characteristic (n) in relation to the total number of observations (N); and the proportion $p = n/N$ is called the probability of having the expected characteristics. Logistic model is based on the cumulative probability function which is mathematically specified as:

$$P_i = \frac{1}{1 + e^{-Z_i}} = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_k X_{ki})}}.$$

It is quite easy to verify that as Z_i ranges from $-\infty$ to $+\infty$, P_i ranges between 0 and 1. Moreover, it can also be transformed as:

$$\frac{P_i}{1 - P_i} = \frac{1 + e^{Z_i}}{1 + e^{-Z_i}} = e^{Z_i}.$$

By taking the natural logarithm of the equation, we have:

$$L_i = \ln(O_i) = \ln\left(\frac{P_i}{1 - P_i}\right) = Z_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_k X_{ki},$$

where L_i is called "logit" and O_i is called "Odds".

Now, assume that at a specific time t , the occurrence probability of the required characteristic is p_t and at $t + 1$, X_j is increased 1 unit while others are kept unchanged. Let's consider, we have:

$$L_{t+1} - L_t = \ln\left(\frac{O_{t+1}}{O_t}\right) = b_j.$$

Consequently, $\frac{O_{t+1}}{O_t} = e^{b_j} \Rightarrow O_{t+1} = O_t \times e^{b_j}$; therefore, the coefficient b_j can be explained as the parameter to determine new Odds from the old Odds by multiplying e^{b_j} ; or equivalently determine the new occurrence probability of the required characteristic

$$p_{t+1} = \frac{p_t e^{b_j}}{1 + p_t(e^{b_j} - 1)}.$$

4. Empirical Experiments and Results

This study utilizes the integrated system proposed by Hien *et al.* [14]; thus, the inputs for the system are from a high quality camera directly mounted in front of driver in such a way that its central axis is set straight forward to driver's face in his/her most comfortable position as shown in Figure 1. The system automatically identifies critical facial features based on an algorithm analyzing face components, the positions of two eyes; and provides these parameters into the system database. Then, the system constantly monitors the states of left eye (denoted by LE) and right eye (denoted by RE) and head postures (denoted by HP) simultaneously. Specifically, for each frame, the system can provide data for the three variables based on a binary classification: 0 and 1, where 0 is the label for open eye or normal head, and 1 is the label for closed eye or nodding head. From the labels of 0 and 1, the system counts the frequency of label 1 in 72 consecutive frames; and based on the practical advice from some experts, if no less than 40 frames of eye states and/or 45 frames of head postures out of the 72 frames are found, the driver is believed to be drowsy; thus, driver's drowsiness state (DR) is labeled with 1, otherwise 0. Consequently, in our regression models, DR is considered as a dependent variable whereas LE , RE , and HP are independent ones; or, our statistical model can be written as

$$DR = f(LE, RE, HP).$$



Figure 1. Integrated system proposed by Hien *et al.* [14]

Our data were collected from 4 systems mounted on 4 heavy trucks operating on the long route between the North and South of Vietnam for 15 days. Every day, each truck had two drivers alternate with each other to drive most of the time. As the system recorded data with specific time shown, after each trip, the drivers were asked to review and confirm whether they felt drowsy at the time. Their confirmation is a critical source of information not only to evaluate the performance of the system but also analyze the relationships between DR and other three variables investigated in this study.

4.1 Multiple Linear Regression

This paper considers two independent linear regression models to find a better one to present the expected relationships. They are:

- (i) $DR = f(LE, RE, HP)$; and

(ii) $DR = f(EY, HP)$ where EY is a variable containing the maximum value of LE and RE at a specific time, i.e. $EY_i = \max\{LE_i, RE_i\}$.

From the experimental data collected, we have two standardized models as the following:

- Model 1: $DR = 0.249 + 0.006LE + 0.006RE + 0.004HP$; and $\bar{R}_1^2 = 0.364$
(0.000) (0.000) (0.000) (0.000)
- Model 2: $DR = 0.115 + 0.011EY + 0.007HP$; and $\bar{R}_1^2 = 0.449$
(0.000) (0.000) (0.000)

where the lower numbers in brackets are the obtained significance levels of relevant regression coefficients.

As $\bar{R}_2^2 > \bar{R}_1^2$ we can conclude that Model 2 is better than Model 1 in presenting the relationship between the drowsiness and the eye state and the head posture. This implies that the eye state in the model should simultaneously consider the state of both eyes to provide better detection ability. Moreover, both models show that the eye state has stronger impact on the drowsiness state of driver. Especially, whenever there is an increase in the frequency of closed eye and/or nodding head, the driver is more likely to be drowsy. The term “more likely” is quantitated with the following binary logistic regression.

4.2 Binary Logistic Regression

As DR is a dichotomous variable with only two possible cases: alert (labeled with 0) and drowsy (labeled with 1), it is hence appropriate to model the probability of a driver falling into drowsiness state based on the variables identified in the above linear regression. Particularly, assume that there are n independent observations; let p_i denote the probability of drowsiness at the i th observation; then, the binary logistic regression can be written as:

$$\ln(O_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_1 EY_i + \alpha_2 HP_i.$$

The Odds $O_i = \frac{p_i}{1-p_i}$ is used to compare the occurrence probability and nonoccurrence probability of drowsiness. The model is named as “BR1”.

Besides, this paper also investigates the interactive influence of the eye state and the head posture on the detection of drowsiness by considering another alternative model which is named “BR2” as

$$\ln(O_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_1 EY_i + \alpha_2 HP_i + \alpha_3 EH_i$$

where $EH_i = EY_i \times HP_i$ is an interactive variable of the eye state and the head posture.

With the data collected in this study, the two logistic models are accordingly presented in Table 1 which shows that both models are statistically significant. From the results in Table 1, with Model BR1, if we have one more frame of closed eye in 72 consecutive frames while the HP is unchanged, the new Odds would increase 1.538 times compared to the old Odds; similarly, if we have one more frame of head posture in 72 consecutive frames while the EY is unchanged, the new Odds would increase 1.330 times compared to the old Odds. This finding can also assist

determining the occurrence probability of drowsiness when we know the probability at a certain time.

Table 1. Regression coefficients of *BR1* and *BR2*

Model	Variable	α	e^α	Sig.
<i>BR1</i>	EY	0.431	1.538	0.000
	HP	0.285	1.330	0.000
	Constant	-19.840	0.000	0.000
<i>BR2</i>	EY	2.331	10.287	0.000
	HP	1.971	7.178	0.000
	EH	-0.040	0.961	0.000
	Constant	-94.872	0.000	0.000

However, in Model *BR2*, explaining the coefficients is a little bit difficult. Let's assume that at a specific time t , we have $EY = 35$ and $HP = 32$. If $EY = 36$, $HP = 32$ at time $t + 1$ (EY increases 1 unit while HP is unchanged), we have

$$L_{t+1} - L_t = \ln\left(\frac{O_{t+1}}{O_t}\right) = \alpha_1 + \alpha_3 HP_t = 10.287 + 0.961 \times 32 = 41.039;$$

meaning that the new Odds would increase $e^{41.039}$ times compared to the old Odds; similarly, if $EY = 35$, $HP = 33$ at time $t + 1$ (HP increases 1 unit while EY is unchanged), we have

$$L_{t+1} - I_t = \ln\left(\frac{O_{t+1}}{O_t}\right) = \alpha_2 + \alpha_3 EY_t = 7.178 + 0.961 \times 32 = 40.813;$$

meaning that the new Odds would increase $e^{40.813}$ times compared to the old Odds. We can also accordingly determine the occurrence probability of drowsiness when we know the probability at a certain time. Therefore, it could be said that the interactive variable can be significantly increase the probability of detecting drowsiness state.

To compare the performance of these two models, we randomly select 389,017 frames from the experimental data collected; among them, 53,210 frames are labeled with 0 (alert), and 335,807 frames are labeled with 1 (drowsy). The two models are employed to label these frames, which are then compared with the original ones to check for their accuracy. Finally, the results are briefly displayed in Table 2 which clearly shows that Model *BR2* outperforms Model *BR1* in term of accurate detection ability. This further supports the significant influence of the interactive variable on the detection ability as mentioned above.

Table 2. Comparison of *BR1* and *BR2*

Model		Observed		% of correctness	
		0	1	Partial	Average
<i>BR1</i>	0	46,335	5,678	87.1	96.8
	1	6,875	330,129	98.3	
<i>BR2</i>	0	51,456	1,707	96.7	99.1
	1	1,754	334,100	99.5	

5. Conclusion

Searching for optimal models to accurately detect and alert driver's drowsiness has been an interesting research topic that attracts special attention of numerous scholars worldwide. Thus, a great number of detection methods have been proposed so far. Among them, visual feature-based approaches, such as eye state, head movement, yawning, facial expressions, etc., have been most preferred as they are non-intrusive and effectively detect drowsiness. However, the current literature fails to show the statistical relationships among the driver's drowsiness, eye state and head posture. Thus, the statistical linear regression and binary logistic regression models found in this paper fill the existing gap; especially, it is found that the eye state should be determined by simultaneously monitoring the eye states of both eyes; and it has greater impact on the detection ability than that of head posture. More importantly, the interactive combination of eye state and head posture provides better detection ability. Our proposed logistic regression model can correctly detect 99.1% of the total investigated observations in a practical experiment study.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed equally and significantly in writing this article. All the authors read and approved the final manuscript.

References

- [1] J. Adachi, T. Hayashi, K. Ogawa, T. Suzuki, H. Ishiguro, T. Nishina, K. Ohue, S. Uozumi, S. Kojima and S. Nakanishi, Development of a sensor detecting eyelid positions, in *15th World Congress on ITS*, Jacob K. Javits Convention Center, New York City (2008).
- [2] B. Benfold and I. Reid, Guiding visual surveillance by tracking human attention, in *Proceedings of 20th British Machine Vision Conference (BMVC2009)* (2009), 14.1–14.11.
- [3] J.V.D. Berg, Sleepiness and head movements, *Industrial Health* **44** (2006), 564–576.
- [4] L.M. Bergasa, J. Nuevo, M.A. Sotelo, R. Barea and M.E. Lopez, Real-time system for monitoring driver vigilance, *IEEE Transactions on Intelligent Transportation Systems* **7** (2002), 63–77.
- [5] B. Bhowmick and K.S.C. Kumar, Detection and classification of eye state in IR camera for driver drowsiness identification, in *Proceedings of the IEEE International Conference on Signal and Image Processing Applications* (2009), 340–345.
- [6] I. Chamveha, Y. Sugano, D. Sugimura, T. Siriteerakul, T. Ohabe, Y. Sta and A. Sugimoto, Head direction estimation from low resolution images with scene adaptation, *Computer Vision Image Understanding* **117** (2013), 1502–1511.
- [7] I.G. Damousis and D. Tzovaras, Fuzzy fusion of eyelid activity indicators for hypovigilance-related accident prediction, *IEEE Transactions on Intelligent Transportation Systems* **9** (2008), 491–500.
- [8] Y. Dong, Z. Hu, K. Uchimura and N. Murayama, Driver inattention monitoring system for intelligent vehicles: A review, *IEEE Transactions on Intelligent Transportation Systems* **12** (2011), 596–614.

- [9] M. Eriksson and N.P. Papanikotopoulos, Eye-tracking for detection of driver fatigue, in *Proceedings of the IEEE Conference on Intelligent Transportation Systems* (1997), 314–319.
- [10] T. Ersal, H.J.A. Fuller, O. Tsimhoni, J.L. Stein and H.K. Fathy, Model-based analysis and classification of driver distraction under secondary tasks, *IEEE Transactions on Intelligent Transportation Systems* **11** (2010), 692–701.
- [11] M.J. Flores and J.M. Armingol, Real-time warning system for driver drowsiness detection using visual information, *Journal of Intelligent and Robotic Systems* **59** (2010), 103–125.
- [12] J.F. Hair, W.C. Black, B.J. Babin and R.E. Anderson, *Multivariate Data Analysis*, 7th edition, Prentice Hall, Upper Saddle River, New Jersey (2010).
- [13] L.T. Hien, T.V. Lang, H.M. Toan and D.N. Toan, Modeling the human face and its application for detection of driver drowsiness, *International Journal of Computer Science and Telecommunications* **3** (2012), 56–59.
- [14] L.T. Hien and D.N. Toan, An algorithm to detect driver's drowsiness based on nodding behaviour, *International Journal of Soft Computing, Mathematics and Control* **5** (2016), 1–8, doi: 10.14810/ijscmc.2016.5101.
- [15] I.F. Ince and T. Yang, A new low-cost eye tracking and blink detection approach: Extracting eye features with blob extraction, *Emerging Intelligent Computing Technology and Applications, LNCS*, **5754** (2009), 526–533.
- [16] J. Jimenez-Pinto and M. Torres-Torriti, Driver alert state and fatigue detection by salient points analysis. in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics* (2009), 455–461.
- [17] J. Jo, S.J. Lee, K.R. Park, I.J. Kim, and J. Kim, Detecting driver drowsiness using feature-level fusion and user-specific classification, *Expert System with Applications* **41** (2014), 1139–1152.
- [18] Q. Ji and X. Yang, Real-time eye, gaze, and face pose tracking for monitoring driver vigilance, *Real-Time Imaging* **8** (2002), 357–377, doi:10.1006/rtim.2002.0279.
- [19] J. Jo, S.J. Lee, H.G. Jung, K.R. Park and J. Kim, A vision-based method for detecting driver's drowsiness and distraction in driver monitoring system, *Optical Engineering* **50** (2011), 127202-1–127202-24.
- [20] J. Jo, S.J. Lee, Y.J. Lee, H.G. Jung, K.R. Park and J. Kim, An edge-based method to classify open and closed eyes for monitoring driver's drowsiness. in *Proceedings of the International Conference of Electronics, Information and Communication (ICEIC)* (2010), 510–513.
- [21] S. Kawato and J. Ohya, Real-time detection of nodding and headshaking by directly detecting and tracking the between-eyes, in *Proceedings of 4th international IEEE Conference on Automatic Face and Gesture Recognition* (2002), 40–45.
- [22] A. Kircher, M. Uddman and J. Sandin, *Vehicle Control and Drowsiness*, Swedish National Road and Transport Research Institute (2002).
- [23] T. Kito, M. Haraguchi, T. Funatsu, M. Sato and M. Kondo, Measurements of gaze movements while driving, *Perceptual and Motor Skills* **68** (1989), 19–25.
- [24] Y. Kurylyak, F. Lamonaca and G. Mirabelli, Detection of the eye blinks for human's fatigue monitoring, in *Proceedings of the IEEE International Symposium on Medical Measurements and Applications (MeMeA)* (2012), 1–4.
- [25] J.W. Li, Eye blink detection based on multiple Gabor response waves, in *Proceedings of the International Conference on Machine Learning and Cybernetics* (2008), 2852–2856.

- [26] C.C. Liu, S.G. Hosking and M.G. Lenn, Predicting driver drowsiness using vehicle measures: Recent insights and future challenges, *Journal of Safety Research* **40** (2009), 239–245.
- [27] K. Minkov, S. Zafeiriou and M. Pantic, A comparison of different features for automatic eye blinking detection with an application to analysis of deceptive behavior, in *Proceedings of the International Symposium on Communications Control and Signal Processing (ISCCSP)* (2012), 1–4.
- [28] E. Murphy-Chutorian, A. Doshi and M.M. Trivedi, Head pose estimation for driver assistance systems: A robust algorithm and experimental evaluation, in *Proceedings of 10th International IEEE Conference on Intelligent Transportation Systems* (2007), 709–714.
- [29] Y. Noguchi, K. Shimada, M. Ohsuga, Y. Kamakura and Y. Inoue, The assessment of driver's arousal states from the classification of eye-blink patterns. in *Proceedings of the International Conference on Engineering Psychology and Cognitive Ergonomics* (2009), 414–423.
- [30] T.D. Orazio, M. Leo, C. Guaragnella and A. Distante, A visual approach for driver inattention detection, *Pattern Recognition* **40** (2007), 2341–2355.
- [31] A. Panning, A. Al-Hamadi and B. Michaelis, A color based approach for eye blink detection in image sequences. in *Proceedings of the IEEE International Conference on Signal and Image Processing Applications (ICSIPA)* (2011), 40–45.
- [32] N. Parmar, *Drowsy Driver Detection System, Engineering Design Project*, Thesis, Ryerson University (2002).
- [33] M. Patel, S.L.L. Lal, D. Kavanagh and P. Rossiter, Applying neural network analysis on heart rate variability data to assess driver fatigue, *Expert Systems with Applications* **38** (2011), 7235–7242.
- [34] W. Rongben, G. Lie, T. Bingliang and J. Lisheng, Monitoring mouth movement for driver fatigue or distraction with one camera, in *Proceedings of the IEEE International Conference on Intelligent Transportation Systems* (2004), 314–319.
- [35] M. Saradadevi and P. Bajaj, Driver fatigue detection using mouth and yawning analysis, *International Journal of Computer Science and Network Security* **8** (2008), 183–188.
- [36] H. Shuyan and Z. Gangtie, Driver drowsiness detection with eyelid related parameters by support vector machine, *Expert Systems with Applications* **36** (2009), 7651–7658.
- [37] K. Smith, S.O. Ba, J.M. Odobez and D. Gatica-Perez, Tracking the visual focus of attention for varying number of wandering people, *IEEE Transactions on Pattern Analysis and Machine Intelligence* **30** (2008), 1212–1229.
- [38] F.M. Sukno, S.K. Pavani, C. Butakoffand and A.F. Frangi, Automatic assessment of eye blinking patterns through statistical shape models, in *ICVS 2009, LNCS* **5815** (2009), 33–42.
- [39] K. Torkkola, N. Massey and C. Wood, Driver inattention detection through intelligent analysis of readily available sensors, *Proceedings of the IEEE International Conference on Intelligent Transportation Systems* (2004), 326–331.
- [40] Y. Tran, A. Craig, N. Wijesuriya and H. Nguyen, Improving classification rates for use in fatigue countermeasure devices using brain activity, in *Proceedings of IEEE International Conference on Engineering in Medicine and Biology Society (EMBC)* (2010), 4460–4463.
- [41] A. Tsuchida, M.S. Bhuiyan and K. Oguri, Estimation of drivers' drowsiness level using a neural network based 'error correcting output coding' method, in *Proceedings of the IEEE International Conference on Intelligent Transportation Systems* (2010), 1887–1892.
- [42] M. Uliyar and S. Ukil, A fast blink detector using canonical correlation analysis, in *Proceedings of the IEEE International Conference on Consumer Electronics (ICCE)* (2012), 33–34.

- [43] E. Vural, M. Çetin, A. Ercil, G. Littlewort, M.S. Bartlett and J.R. Movellan, Drowsy driver detection through facial movement analysis, in *Proceedings of the IEEE International Conference on Human-Computer Interaction* (2007), 6–18.
- [44] L. Wang, X. Ding, C. Fang and C. Liu, Eye blink detection based on eye contour extraction, *Proceedings of SPIE Image Processing: Algorithms and Systems VII* 7245.72450R (2009), 1–7.
- [45] W.W. Wierwille, L.A. Ellsworth, S.S. Wreggit, R.J. Fairbanks and C.L. Kim, Research on vehicle-based driver status/performance monitoring: development, validation, and refinement of algorithms for detection of driver drowsiness, National Highway Traffic Safety Administration, (1994), *Final Report: DOT HS 808 247*.
- [46] J.D. Wu and T.R. Chen, Development of a drowsiness warning system based on the fuzzy logic images analysis, *Expert Systems with Applications* **34** (2008), 1556–1561.
- [47] J. Wu and M.M. Trivedi, Simultaneous eye tracking and blink detection with interactive particle filters, *EURASIP Journal on Advances in Signal Processing* (2008), 823695-1–823695-20.
- [48] J.H. Yang, Z.H. Mao, L. Tijerina, T. Pilutti, J. Coughlin and E. Feron, Detection of driver fatigue caused by sleep deprivation, *IEEE Transactions on Systems, Man, Cybernetics. A, Systems Humans* **39** (2009), 694–705.
- [49] L. Yunq, Y. Meiling, S. Xiaobing, L. Xiuxia, O. Jiangfan, Recognition of eye states in real time video. in *Proceedings of the International Conference on Computer, Engineering and Technology* (2009), 554–559.