Facial Expression Measurement for Detecting Driver Drowsiness

Satori Hachisuka[1], Kenji Ishida[1], Takeshi Enya[1], and Masayoshi Kamijo[2]

[1] DENSO CORPORATION, Research Laboratories
500-1, Minamiyama, Komenoki-cho, Nisshin-shi, Aichi-ken, 470-0111, Japan
[2] Interdisciplinary Graduate School of Science and Technology, Shinshu University
3-15-1, Tokida, Ueda-shi, Nagano-ken, 386-8567, Japan
arimitsu@rlab.denso.co.jp

Abstract. This paper presents the method of detecting driver's drowsiness level from facial expressions. Our method is executed according to the following flow: taking a driver's facial image, tracing the facial features by image processing, and classifying the driver's drowsiness level by pattern classification. We found that facial expression had the highest linear correlation with brain waves as the general index of drowsiness during monotonous driving. After analyzing the facial muscle activities, we determined 17 feature points on face for detecting driver drowsiness. A camera set on a dashboard recorded the driver's facial image. We applied Active Appearance Model (AAM) for measuring the 3-dimensional coordinates of the feature points on the facial image. In order to classify drowsiness into 6 levels, we applied k-Nearest-Neighbor method. As a result, the average Root Mean Square Errors (RMSE) among 13 participants was less than 1.0 level. Our method also detected the driver's smile.

Keywords: Facial expression, Facial muscle, Driver drowsiness, Drowsiness detection.

1 Introduction

Although active safety systems in vehicles have contributed to the decrease in the number of deaths occurring in traffic accidents, the number of traffic accidents is still increasing. Driver drowsiness is one reason for such accidents and is becoming an issue. The National Highway Traffic Safety Administration (NHTSA) estimates that approximately 100,000 crashes each year are caused primarily by driver drowsiness or fatigue in the United States [1]. In Japan, attention lapse, including that due to driving while drowsy, was the primary reason for traffic accidents in 2008. The Ministry of Economy, Trade and Industry in Japan reports that the number of such accidents has increased 1.5 times in the 12-year period from 1997 to 2008 [2].

One solution to this serious problem is the development of an intelligent vehicle that can predict driver drowsiness and prevent drowsy driving. The percentage of eyelid closure over the pupil over time (PERCLOS) is one of the major methods for the detection of the driver's drowsiness [3]. We developed a method for the detection

D. Harris (Ed.): Engin. Psychol. and Cog. Ergonomics, HCII 2011, LNAI 6781, pp. 135–144, 2011.

of driver drowsiness using the whole facial expression, including information related to the eyes. This method is based on the results of observational analysis. The results of this analysis revealed that features of drowsiness appear on the eyebrows, cheeks, and mouth, in addition to the eyes [4]. The aim of using the facial expression is to detect drowsiness in the early stages, on the basis of the many minute changes in the facial parts. Our goal is to develop an intelligent safety vehicle that can relieve drivers from struggling against drowsiness by detecting their drowsiness and keeping them awake naturally by providing feedback system. In this paper, we discuss a method for detecting driver drowsiness in the early stages. Our method detects drowsiness with accuracy equivalent to that of brain waves, which is the general index of drowsiness. The method categorizes drowsiness into 6 levels using features of facial expression based on the mechanism of facial muscle activities without any attached sensors. We developed the drowsiness detection method with a system comprising a camera set on a dashboard, an image processing algorithm, and a drowsiness detection algorithm.

This paper presents a novel drowsiness detection method and assesses its effectiveness.

2 Early-Stage Drowsiness Detection

The changes in brain waves, especially alpha waves, are one of the indices used to detect changes in the level of drowsiness [5]. Although change in brain waves is an effective index for detecting drowsiness, it is not feasible to apply this index in a vehicle because of the electrodes that are used as contact-type sensors. However, it is recognized in the field of cerebral neuroscience that the facial nerve nucleus is contained in the brain stem, which is defined as an organ of drowsiness [6]. Therefore, we adopted facial expression as the index of drowsiness as an alternative to brain waves. In addition, it is apparent from our experience that we can recognize drowsiness in others from their facial expressions.

In Japan, Kitajima's trained observer rating is a commonly used method for the detection of driver drowsiness on the basis of appearance [7]. The method divides drowsiness into 5 levels with criteria such as "slow blink", "frequent yawning", and so on. Since these criteria are qualitative, the method is not appropriate for automatic detection of drowsiness. Therefore, the quantitative method to detect facial expression was required. To determine the best index as an alternative to brain waves, we examined the correlation between brain waves and other indices such as PERCLOS, heart rate, lane deviation, and facial expression [8]. Those indices do not require the attachment of sensors [3, 9-15]. According to the result, facial expression has the highest correlation with brain waves (correlation coefficient = 0.90) and it detects drowsiness at an earlier stage than other indices. This indicates that facial expression is the most appropriate index to use for the detection of driver drowsiness in the early stages. Therefore, to be able to predict and prevent drowsy driving, the development of a method that detects driver drowsiness from facial expression is necessary.

3 Automatic Drowsiness-Detection Using Facial Expression

It was necessary to solve 3 problems for the development of an automatic drowsiness-detection system:

1. How to define the features of drowsy expression.
2. How to capture the features from the driver's video-recorded facial image.
3. How to estimate the driver's drowsiness index from the features.

Our approaches to solving these problems are explained in this chapter.

3.1 Features of Drowsy Expression

We clarified the particular features of drowsy expression by comparing the facial muscle activities of the waking expression with those of the drowsy expression [16]. We measured 9 facial muscles of each of 17 volunteer participants during the task of monotonous driving in the driving simulator for 1 hour. The left side of Fig. 1 shows the site of 9 facial muscles; inner frontalis, upper orbicularis oculi, lower orbicularis oculi, zygomaticus major, masseter, risorius, upper orbicularis oris, lower orbicularis oris, and mentalis. We divided the reference states of drowsiness into 6 levels, i.e., "Not Sleepy", "Slightly Sleepy", "Sleepy", "Rather Sleepy", "Very Sleepy", and "Sleeping" by adding the "Sleeping" level to Kitajima's trained observer rating scale [7].

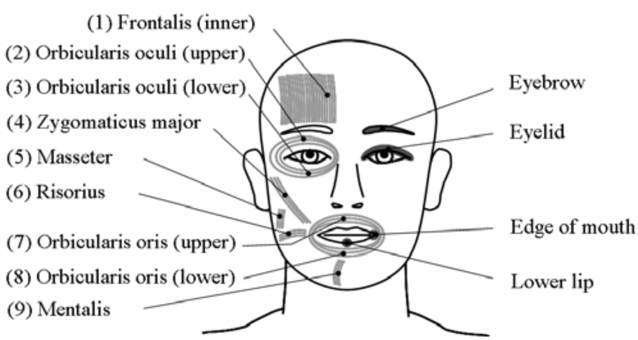
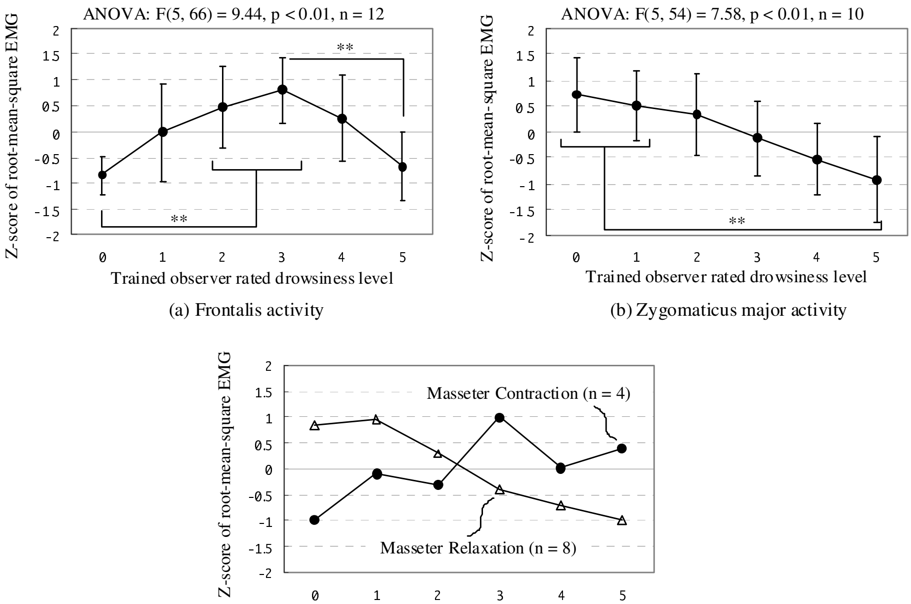


Fig. 1. Sites of 9 facial muscles and 4 facial features. Facial muscles were measured by facial electromyograph.

Figure 2 shows the comparison results of the drowsiness levels and the facial muscle activities. The contractions of the frontalis and the relaxation of the zygomaticus major were detected in more than 75 percent of participants, and the relaxation or contraction of the masseter muscle was detected in 82 percent of participants. In addition, contraction of the frontalis, which was detected in 94 percent of participants, was the characteristic expression of resisting drowsiness. This characteristic expression does not appear during the natural drowsy state without any struggle against drowsiness. According to the result, we chose the eyebrows, edges of the mouth, and the lower lip as the facial features related to the frontalis, zygomaticus major, and masseter, respectively, in addition to the eyelids, which are the general features of the drowsiness expression (The right side of Fig.1).



(a) Frontalis activity (b) Zygomaticus major activity

(c) Masseter activity

Fig. 2. Typical comparison results of the drowsiness levels and the facial muscle activities. The contractions of frontalis and the relaxation of zygomaticus major were detected in more than 75 percent of participants, and the relaxation or contraction of the masseter muscle was detected in 82 percent of participants.

3.2 Image Processing for Measuring Features of Drowsy Expression

We developed a method of image processing for measuring the features of drowsy expression, without any sensor contact, from a driver's video-captured facial image [17]. The method, which is based on the Active Appearance Model (AAM) [18], detects 3-dimensional coordinates of measurement points on the driver's face per frame. Our AAM consists of the specific 2-dimensional model and the generic 3-dimensional model. The specific 2-dimensional model has information relating to the shape and texture of the individual driver's facial image. The generic 3-dimensional model has the 3-dimensional vectors of each measurement points. We developed a method that extracts change in facial expression without individual differences in the shape of each driver's face by using the generic 3-dimensional model. This method is an effective way of detecting the coordinates of the points on the face in the vehicle, which is expected to be driven by an unspecified number of drivers. The process of this method is shown in Fig. 3. First, the specific 2-dimensional model is generated by a captured static facial image of the driver. This process is performed once for each driver. Next, the specific 2-dimensional model is fitted on each frame of the driver's facial image and the 2-dimensional coordinates of the measurement points are output. Finally, the generic 3-dimensional model is aligned based on the 2-dimensional coordinates and the 3-dimensional coordinates of each measurement points are output per frame. We employed the method of steepest descent to the fitting of the specific 2-dimensional model and the aligning of the generic 3-dimensional model.

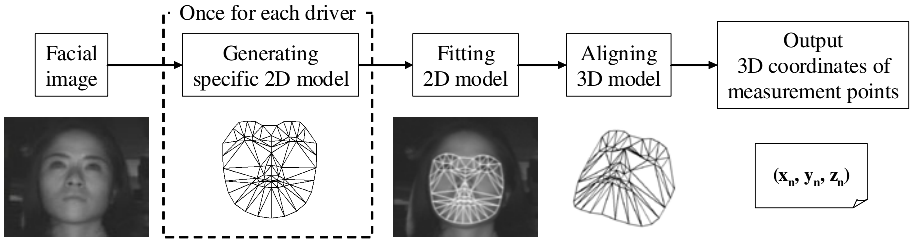


Fig. 3. Flow of the image processing with AAM

3.3 Method of Detecting Drowsiness Level

We adopted 17 points as the measurement objects to detect the drowsy expression. Figure 4 shows the 17 points: 10 points on the right and left eyebrows (5 points on each side), 4 points on the right and left eyelids (2 points on each side), 2 points on the right and left edges of the mouth (1 point on each side), and 1 point on the lower lip. As the features of drowsy expression we used scalar quantities of the change in the 17-point 3-dimensional positions, which were measured from the positions on the waking-state expression. The individual differences of the waking-state expressions are reduced by defining the positions on the waking-state expressions as reference positions. We employed the k-Nearest-Neighbor method, which is one of the pattern classification methods, for detecting the drowsiness level. This decision was based on the result of a preliminary experiment in which we compared the results of the drowsiness levels detected by the trained observer with other estimation methods: multiple regression analysis method, subspace method, and k-Nearest-Neighbor method. The drowsiness level estimated by the k-Nearest-Neighbor method had the highest correlation with the referential drowsiness level as estimated by the trained observer. Our method uses the prebuilt database that consists of the 6-level drowsy expression features of several individuals. The driver's features are compared with the whole database, and the similarities of each comparison are applied to detect the drowsiness level. The similarity-based method is able to detect drowsiness with higher time resolution than the method using trends in the change in the facial expression at a specific time interval, such as 30 seconds [19].

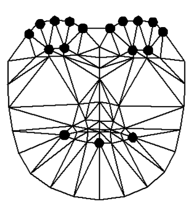


Fig. 4. Seventeen measurement points for detecting drowsy expressions

The every 5-second (150-frame) average features are used as the feature data in this method. The 5-second block time is applied as the bare minimum sampling time for the trained observer rating for facial expressions [7]. According to the averaging, it is possible to detect the difference between “eye closure based on blinking” and “eye closure based on drowsiness”, which is difficult to distinguish from a still frame.

We investigated the accuracy of our drowsiness detection. We used the driving simulator in a sound-proof room. Motion system was excluded from the driving simulator to induce drowsiness in the participants efficiently and to measure basic data of participants’ drowsy expressions accurately. The driving task was also designed monotonously for the purpose of inducing drowsiness in the participants efficiently. The longitudinal flows of two sine curves, from the top to the bottom of the screen, were projected on the screen. The circle indicating the position of the vehicle from an overhead view was also projected on the screen between the sine curves. We instructed the participants to operate the driving simulator with the steering wheel to maintain their position between the sine curves. The participants’ facial images were recorded by the digital video camera (480 x 640 pixels, 30 fps, progressive scan) on the dashboard. The participants were instructed to remain awake during the driving and maintain the same position they would adopt while driving a real vehicle, even if they became drowsy. As a reference for the 6 drowsiness levels, we used the results of ratings for the drivers’ recorded facial images from 2 trained observers. The 13 volunteer participants had drivers’ licenses and were aged in their 20s to 40s. They were informed of simulator sickness before the experiments and required to sign an informed consent document. During the experiments, at least one examiner observed the participant’s appearance from outside the sound-proof room. After the experiment, the participant rested with the examiners for approximately 10-15 minutes.

Drowsiness detection was performed off-line using the leave-one-out cross validation procedure with the features, which were calculated by referring to the 13 participants’ recorded facial images. All of the 13 participants fell asleep during the experiment. In the leave-one-out cross validation, data for 12 arbitrarily chosen participants were used as training data and used to detect the drowsiness of the remaining participant, who was excluded from the training data; this was performed repeatedly. The training data consist of the 5-second average features (3-dimensional displacement of 17 points) and the reference of the drowsiness levels, which are labeled on the features. The flow of drowsiness detection is given as follows. The entered driver’s features are compared with all of the training data. The top 80 training data, which have a strong similarity to the driver’s features, are picked up. The driver’s drowsiness level is estimated based on a majority decision of what the referential drowsiness levels are, which are labeled on the 80 training data. We employed the Euclidean distance as the index of similarity between the driver’s features and the features of the training data. A small distance indicates strong similarity.

We investigated the effectiveness of the method by comparing the detected drowsiness level with the referential drowsiness level. To detect the facial change based on the drowsiness accurately, we clipped the parts of the video of the participants’ facial images before the comparison, and detected the drowsiness levels from those partial videos. The 3 criteria for clipping the partial videos were as follows.

- The facial image of the driver in a front-facing position.
- The facial image without any occlusion such as a steering wheel and/or a hand.
- The facial image without any actions that cause facial change, such as yawning and smiling.

The Root Mean Square Errors (RMSE) of 13 participants are shown in Table 1. These results demonstrate that our method detects the drowsiness with a RMSE of less than 1.0 for 9 participants. The average RMSE among 12 participants is 0.91. On the other hand, RMSE was increased when we used fewer or more feature points than 17 such as 10 points on eyebrows, 4 points on eyelids, or all measurement points on whole face to detect the drowsiness. Therefore, 17 points, which described in chapter 3.3 (FIg. 4), were the best features for our drowsiness-detection method. In addition, we found that if the participant didn't fall asleep during the examination, and its referential drowsiness levels were under level 2 ("Sleepy"), our method indicated the drowsiness levels under level 3 ("Rather Sleepy"). In this paper, this case occurred in only one participant aside from 13 participants.

Table 1. Root Mean Square Errors of drowsiness detection

Participant #	Root Mean Square Error (RMSE)
1	1.06
2	0.90
3	1.14
4	0.91
5	0.78
6	1.11
7	0.71
8	1.00
9	0.82
10	0.81
11	0.93
12	0.77
13	0.85
Average	0.91
SD	0.14

4 Cancellation of Awake Expressions

As we described in the previous chapters, we demonstrated that our method could detect the drowsiness level, when the drowsy expression was input. On the other hand, it is well-known that the facial expressions are divided into 6 global common categories [20] or 9 psychological categories [21]. Since our method only focused on the drowsiness category and the classification of the level, we additionally investigated the result when the facial expression, which was not related to the drowsy expression, was input to our method. We applied "smile" with the entirely awake state as the input expression. The smiling facial images of 4 volunteer participants were recorded by the same camera and the same setup as mentioned in chapter 3.3. The participants consisted of 2 males and 2 females, and were aged in their 20s to 40s. All participants were entirely awake. We input 10-second (300-frame) facial images per participant to our method. As shown in the "Normal output" column on Table 2, the output results were drowsiness level 3 ("Sleepy") or 4 ("Very Sleepy"), respectively instead of the level 0 ("Not Sleepy"). As a feasible method in a real vehicle, these output results must be level 0 or "smile", when a driver smiles in the entirely awake state. The reason of these false detections may be that the facial features such as narrowed eyes and opened mouth were similar to those of drowsy expression.

For the purpose of making a categorical distinction between drowsiness and smile, we examined the difference among the 3-dimensional displacement of 17 facial points. We found that y-axis displacement of the edges of mouth were the most and the second quantity among the facial points. In addition, the threshold of the quantity was over 1.5 (non unit of quantity required) in the 3-dimensional method in this paper. We attached a filter to our method for distinguishing "smile" from "drowsiness" when the displacements of 3-dimensional feature points and the threshold meets the conditions mentioned above. Due to the effect of this filter, we could detect "smile" with 100 percent accuracy among 4 volunteer participants' facial expressions (Table 2). In the similar way, we confirmed the possibility of detecting "speech" with the variance of y-axis displacement of the feature point on lower lip in a few participants.

Table 2. Detected Drowsinesslevel and Expression

Participant #	Normal output		Filtered output	
	0 - 5 [sec]	5 - 10 [sec]	0 - 5 [sec]	5 - 10 [sec]
1	Level 3	Level 4	Smile	Smile
2	Level 3	Level 3	Smile	Smile
3	Level 3	Level 4	Smile	Smile
4	Level 3	Level 4	Smile	Smile

5 Conclusion

In this paper, we presented the driver's drowsiness detection method using facial expression, and we established the effectiveness of this method experimentally. Our method is executed according to the following flow: taking a driver's facial image, tracing 17 feature points by image processing, and rating the driver's drowsiness according to a 6-level scale from the features by pattern classification. The results of the drowsiness detection correspond to the drowsiness reference as estimated by a trained observer with an average RMSE of less than 1.0 level among 13 participants. The distinguishing feature of our method is that it uses 17 facial features based on the activities of facial muscles. In addition, we attached the filter to our method for distinguishing “smile” from “drowsiness” when the facial expression, which was not related to the drowsy expression, was input. This filter effectively detected “smile” with 100 percent accuracy among 4 participants.

The limitations of this paper were the reality of driving environment and the number of the participants. In future work, we will verify practical effectiveness of our drowsiness detection method using motion-based driving simulator and/or real car. In that phase, we will have to distinguish drowsy expression from complexly-mixed expressions. Because, there is a possibility to appear the mixed expressions on drivers’ faces, such as “smiling with drowsiness”, “speaking with drowsiness” and so on, during the natural expressions in real car. Additionally, we will increase the number of participants in our experiments and develop the effective training data for detecting drowsiness of a large number of drivers.

It is also necessary to develop a feedback system to achieve an intelligent safety vehicle that can relieve drivers struggling against drowsiness. We have now started to develop a feedback system that keeps the driver awake effectively and naturally. In addition, the integration of personal verification into our method will lead to the development of a highly precise drowsiness-detection method.

References

1. U.S. Department of Transportation: Intelligent Vehicle Initiative 2002 annual report. `http://www.itsdocs.fhwa.dot.gov//JPODOCS/REPTS_TE//13821.pdf`
2. The Ministry of Economy, Trade and Industry: Technological Strategy Map (2009), `http://www.meti.go.jp/policy/economy/gijutsu_kakushin/kenkyu_kaihatu/str2009/7_1.pdf` (in Japanese)
3. Wierwille, W.W., Ellsworth, L.A., Wreggit, S.S., Fairbanks, R.J., Kirn, C.L.: Research on Vehicle-Based Driver Status/Performance Monitoring; Development, Validation, and Refinement of Algorithms For Detection of Driver Drowsiness: National Highway Traffic Safety Administration Final Report, DOT HS 808 247 (1994)
4. Ishida, K., Ito, A., Kimura, T.: A Study of Feature Factors on Sleepy Expressions based on Observational Analysis of Facial Images. Transactions of Society of Automotive Engineers of Japan 39(3), 251–256 (2008) (in Japanese)
5. Eoh, H.J., Chou, M.K., Kim, S.H.: Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. International Journal of Industrial Ergonomics 35, 307–320 (2005)
6. Saper, C.B., Chou, T.C., Scammell, T.E.: The sleep switch: hypothalamic control of sleep and wakefulness. TRENDS in Neurosciences 24(12), 726–731 (2001)
7. Kitajima, H., Numata, N., Yamamoto, K., Goi, Y.: Prediction of Automobile Driver Sleepiness (1st Report, Rating of Sleepiness Based on Facial Expression and Examination of Effective Predictor Indexes of Sleepiness). The Japan Society of Mechanical Engineers Journal (Series C) 63(613), 93–100 (1997) (in Japanese)
8. Ishida, K., Hachisuka, S., Kimura, T., Kamijo, M.: Comparing Trends of Sleepiness Expressions Appearance with Performance and Physiological Change Caused by Arousal Level Declining. Transactions of Society of Automotive Engineers of Japan 40(3), 885–890 (2009) (in Japanese)

9. Sato, S., Taoda, K., Kawamura, M., Wakaba, K., Fukuchi, Y., Nishiyama, K.: Heart rate variability during long truck driving work. Journal of Human Ergology 30, 235–240 (2001)
10. Kozak, K., Pohl, J., Birk, W., Greenberg, J., Artz, B., Blommer, M., Cathey, L., Curry, R.: Evaluation of lane departure warnings for drowsy drivers. In: Proceedings of the Human Factors and Ergonomics Society 50th annual meeting, pp. 2400–2404 (2006)
11. Liu, C.C., Hosking, S.G., Lenne, M.G.: Predicting driver drowsiness using vehicle measures: Recent insights and future challenges. Journal of Safety Research 40, 239–245 (2009)
12. Ueno, A., Manabe, S., Uchikawa, Y.: Acoustic Feedback System with Digital Signal Processor to Alert the Subject and Quantitative Visualization of Arousal Reaction Induced by the Sound Using Dynamic Characteristics of Saccadic Eye Movement: A Preliminary Study. In: IEEE Engineering in Medicine and Biology 27th Annual Conference, China, pp. 6149–6152 (2005)
13. Bergasa, L.M., Nuevo, J., Sotelo, M.A., Barea, R., Lopez, M.E.: Real-Time System for Monitoring Driver Vigilance. IEEE Transactions on Intelligent Transportation Systems 7(1), 63–77 (2006)
14. Ji, Q., Zhu, Z., Lan, P.: Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue. IEEE Transactions on Vehicular Technology 53(4), 1052–1068 (2004)
15. Arimitsu, S., Sasaki, K., Hosaka, H., Itoh, M., Ishida, K., Ito, A.: Seat Belt Vibration as a Stimulating Device for awakening Drivers. IEEE/ASME Transactions on Mechatronics 12(5), 511–518 (2007)
16. Ishida, K., Ichimura, A., Kamijo, M.: A Study of Facial Muscular Activities in Drowsy Expression. International Journal of Kansei Engineering 9(2), 57–66 (2010)
17. Kimura, T., Ishida, K., Ozaki, N.: Feasibility Study of Sleepiness Detection Using Expression Features. Review of Automotive Engineering 29(4), 567–574 (2008)
18. Cootes, T.F., Edwards, G.J., Taylor, C.J.: Active appearance models. IEEE Transactions on Pattern Analysis and Machine Intelligence 23(6), 681–685 (2001)
19. Vural, E., Cetin, M., Ercil, A., Littlewort, G., Bartlett, M., Movellan, J.: Automated Drowsiness Detection For Improved Driving Safety. In: 4th International conference on Automotive Technologies, Turkey, pp. 13–14 (2008)
20. Ekman, P., Friesen, W.V.: Unmasking the Face. Prentice Hall, New Jersey (1975)
21. Russell, J.A., Weiss, A., Mendelsohn, G.A.: Affect Grid: A Single-Item Scale of Pleasure and Arousal. Journal of Personality and Social Psychology 57(3), 493–502 (1989)