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Estimation of Drowsiness Level Based on Eyelid Closure and Heart Rate Variability

Ayumi Tsuchida, Md. Shoaib Bhuiyan and Koji Oguri

***Abstract*— This paper presents a novel method that uses eyelid closure and heart rate variability to estimate the driver's drowsiness level. Laboratory experiments were conducted by using a proprietary driving simulator, which induced drowsiness among the test drivers. The purposes of these experiments were to obtain the electrocardiogram (ECG) and the eye-blink video sequences. Also the drivers were monitored through a video camera. The changes in facial expression of the drivers were used as a standard index of drowsiness level.**

Error-Correcting Output Coding (ECOC) was employed as a multi-class classifier to estimate the drowsiness level. We extended the ordinary ECOC using a loss function for decoding procedure to obtain class tendencies of each drowsiness level. We used the Loss-based Decoding ECOC (LD-ECOC) to classify the drowsiness level. As a result, we obtained an extraordinarily high accuracy for estimation of drowsiness level.

I. Introduction

TRAFFIC accidents have been most commonly caused by human errors, and the number of accidents has still remained high. The reduction of the traffic accidents is an important issue. Many studies have therefore been conducted to construct safe driving systems. Among the factors of the traffic accidents, driver's drowsiness is considered to be an important factor which contributes to serious traffic accidents. Bhuiyan [1] surveyed a large body of research on eye-activity based drowsiness detection methods. Detecting the driver's drowsiness is an effective way to prevent traffic accidents. Some methods concerning the detection of drowsiness based on facial expression or in combination of other physiological signals have been proposed [2][3]. Wake or sleep; only these two stages are dealt in [2], while [3] does not do any clustering. Pattern recognition is one of the means to classify the degree of drowsiness. Current level of pattern recognition (for detecting driver's drowsiness) has limitation in accuracy. In order to solve this problem, we suggest the high-accuracy classification method for the estimation of drowsiness level based on the eyelid closure and heart rate variability.

Error-Correcting Output Coding (ECOC) was employed as a multi-class classifier to estimate the drowsiness level. The ordinary ECOC uses a hamming distance for decoding procedure, so we call this approach Hamming Decoding ECOC (HD-ECOC). In the present research, we extended the ordinary ECOC to obtain class tendencies of each drowsiness level using a loss function for decoding procedure. We call this approach Loss-based Decoding ECOC (LD-ECOC). The ability of our proposed method was examined with the driving simulator. By reference to the driver's facial expression, the accuracy of HD-ECOC and LD-ECOC are calculated for performance comparison.

Ayumi Tsuchida is with the Graduate school of Information Science and Technology, Aichi Prefectural University, Aichi 480-1198, JAPAN (e-mail: a.tsuchida@bme.ist.aichi-pu.ac.jp).

Md. Shoaib Bhuiyan is with the Faculty of Medical Engineering, and also with the Graduate School of Medical Imaging, Suzuka University of Medical Science, Mie 510-0293, JAPAN (e-mail: bhuiyan@suzuka-u.ac.jp).

Koji Oguri is with Faculty of Information Science and Technology, Aichi Prefectural University, Aichi, JAPAN (e-mail: oguri@ist.aichi-pu.ac.jp).

TABLE I
DROWSINESS LEVEL FROM FACIAL EXPRESSIONS

Drowsiness level	Example of movements
1: not drowsy	Moving eye-gaze quickly and frequently
2: slightly drowsy	Opening mouth, moving eye-gaze slowly
3: moderately drowsy	Blinking eyes slowly and frequently, moving their mouth
4: rather drowsy	Likely conscious blink, tossing their head, yawning
5: very drowsy	Closing eyelid, leaning head to backward or forward

II. Drowsiness Level and Physiological Signals

A. Drowsiness Level from Facial Expressions

We used the subjective drowsiness rating from facial expression as criteria of drowsiness level. This rating method was defined by Japan's NEDO (New Energy and Industrial Technology Development Organization) [5]. This method have high correlation coefficient between the subjective drowsiness and real drowsiness [6], and has already been used in several studies [7][8]. Zilberg [4] also reported subjected ratings, which we found consistent with NEDO definition (we used, in Table I) of drowsiness levels from facial expression.

B. Physiological Features Applied to the Estimation

Physiological signals enable to detect a variety of changes in the mental and physical states of human subjects. We focused on the eyelid closure and the heart rate variability.

The degree of eyelid closure increases when people become drowsy. Figure 1 shows a typical relationship of drowsiness level from facial expression and the degree of eyelid closure. We employed this concept as input features of the estimation method. The eyelid closure level is measured by analysis of eye-blink video sequence. We used the faceLAB system by Seeing Machines for analysis. This system delivers the degree of eyelid closure data at a sampling frequency of 60 Hz as normalized value from 0 to 1.

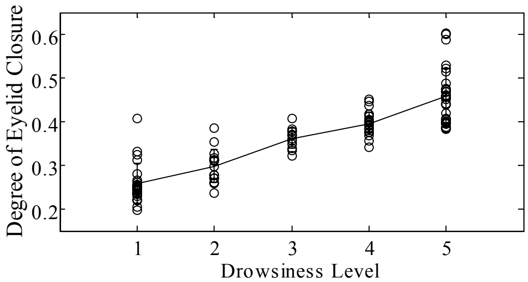

Fig. 1. An example of relationship between drowsiness level and degree of eyelid closure.

In general, autonomic functions are influenced when people feel drowsy. Consequently, the most controversial part of drowsiness indicator is the autonomic nerve activity. However, the direct observation of the autonomic nerve activity is extremely difficult. Therefore, we focused on the heart rate variability as a superficial reflection of the autonomic nerve activity. However, the direct observation of the autonomic nerve activity is extremely difficult. Therefore, we focused on the heart rate variability as a superficial reflection of the autonomic nerve activity.

Since Heart Rate Variability (HRV) is acquired by analyzing RR Interval (RRI), we measured the electrocardiogram (ECG). From spectrum of HRV signals, we obtained Low-Frequency (*LF*) components between 0.04Hz and 0.15Hz, and High-Frequency (*HF*) components between 0.15Hz and 0.45Hz. *LF* components are influenced by sympathetic nerve and parasympathetic nerve, and *HF* component is influenced by parasympathetic nerve [9]. Equations (1) and (2) are commonly used as indicators of Sympathetic Nervous Activity (*SNA*) and Parasympathetic Nervous Activity (*PNA*).

$$SNA = \frac{LF}{HF} \tag{1}$$

$$PNA = HF \tag{2}$$

In this study, we used mean value of RRI, variance of RRI, *SNA* and *PNA* as input features of the estimation method.

III. Multi-classification Technique

A. Multi-classification technique by a combination of binary-classifiers

There is not yet a definitive method for solving multi-discriminant problem, although AdaBoost and Support Vector Machine (SVM) are generally used. Hence, many researchers have proposed various multi-classification techniques until now. ECOC is one of the means of extending the binary classifier to multi-classifier. Figure 2 shows a diagrammatic illustration of ECOC. This method transforms the binary classifier data to multi-classifier data based on the code table, and it enables to extension simply by modifying the code table. Subsection *B* describes the HD-ECOC proposed by Dietterich [10], and then subsection *C* describes the LD-ECOC.

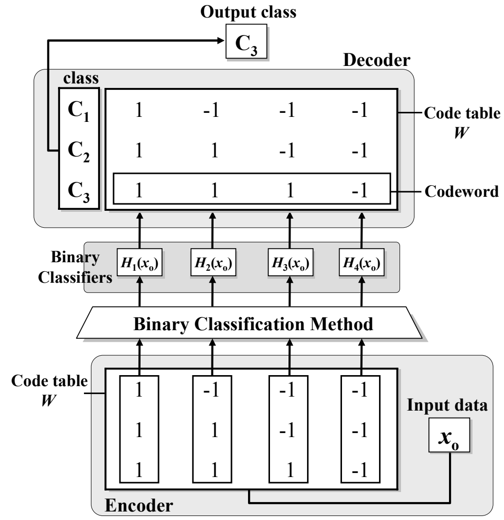

Fig. 2. A diagram of multi-class recognition method based on ECOC by means of binary classifiers.

B. Hamming Decoding ECOC (HD-ECOC)

Now we elaborate how to deal with multi-discriminant problem among *G* classes (*G*>2) in the following passage.

Firstly, training sample is given by Equation (3).

$$(X, Y) \equiv \{x^i, y^i\}_{i=1}^{n} \tag{3}$$

When the number of the classifier is expressed as the notation *p*, the multi-discriminant problem is solved by the $p \times G$ dimensional matrix, $W \in \{1, -1\}^{p \times G}$ which is called code table. If *G*=3, the notation *W* is defined by Equation (4).

$$W = \begin{pmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{pmatrix} \tag{4}$$

The class labels are decomposed into the *p* dimensional vector $z = Ws$.

Secondly, listed below are the definitions of the required notations. The sets of coding labels is defined as $Z = WS$, and the notation z_j^i means the *j*th element of the *i*th coding label $z^i = Ws^i$. When we analyze based on the code table *W*, learning is conducted by using the input vectors *X* and the *j*th element of *Z* as the training labels. Although coding labels z_j^i consist of 1 or -1, the coding method including 0 is proposed by Allwein et al. [11]. When this method is used for coding procedure, we obtain the expression *W* as Equation (5).

$$W = \begin{pmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \\ 1 & -1 & 0 \\ 1 & 0 & -1 \\ 0 & 1 & -1 \end{pmatrix} \tag{5}$$

When this code table is used for training, only the training samples represented by $z_j^i = (1|-1)$ are adopted for training. In the training procedure, we obtain the hypothesis $H(X)$ by the binary classifier, AdaBoost or SVM.

Finally, the label of class G is obtained from whole hypothesis based on the hamming distance for decoding. The hamming distance d_H^i is defined as Equation (6).

$$d_H^i(W(r), H(X)) = \sum_{j=1}^{p} \left(\frac{1 - \text{sign}(W(r,j) h_j^i(x^i))}{2} \right) \tag{6}$$

where $W(r)$ is rth columns of the matrix W. $h_j^i(x^i)$ is the hypothesis of z_j^i. Through the decoding procedure, the results of classification are obtained as Equation (7).

$$\hat{y}^i = \arg\min_r d_H^i(W(r), H(X)) \tag{7}$$

C. Loss-Based Decoding ECOC (LD-ECOC)

Since signum function is employed in Equation (6) for decoding procedure, the output of the hypothesis are binary values, either 1 or -1. Concerning the binary classifier such as AdaBoost and SVM, the Hamming distances between the hyperplane and input feature vectors indicate the degree of reliability [12]. While estimating the drowsiness level, it is regarded as being effective to obtain class tendencies of each class. Thus, we propose the LD-ECOC, treating the hypothesis $h(x)$ as a problem of loss function. Loss value d_L^i is defined as Equation (8).

$$\begin{aligned} d_L^i(W(r), H(X)) &= \sum_{j=1}^{p} \begin{cases} \exp(|h_j^i(x^i)|) & \text{if} \quad W(r,j)h_j^i(x^i) < 0 \\ -\exp(|h_j^i(x^i)|) & \text{if} \quad W(r,j)h_j^i(x^i) > 0 \\ 0 & \text{if} \quad W(r,j)h_j^i(x^i) = 0 \end{cases} \\ &= \sum_{j=1}^{p} -\text{sign}(W(r,j)h_j^i(x^i)) \exp(|h_j^i(x^i)|) \end{aligned} \tag{8}$$

Through the decoding procedure, the results of classification are obtained as Equation (9).

$$\hat{y}^i = \arg\min_r d_L^i(W(r), H(X)) \tag{9}$$

IV. Experiment of Simulated Monotonous Driving

A. Experimental conditions

Section III described the specific algorithm of our proposed method. Our next step was to evaluate how accurately this method would estimate the drowsiness level. In order to examine the performance of the method, we conducted the experiments using the driving simulator. Five test drivers (three males and two female) were instructed to assume a normal driving position while being subjected to simulated monotonous driving at a constant speed on a test-course. Time duration was 20 minutes each, and we conducted 10 different experiments with each test driver. Figure 3 shows the overview of the driving simulator. A screen was placed in front of the driver's seat to display a computer-generated motion picture of monotonous freeway driving (Figure 4), which induces drowsiness in the driver. Test drivers indeed got drowsy within 20 minutes. This might be because in real life, drivers look not only in front of their car, but also glance sideways while driving. This relieves their eye from some strain that does not get relieved while in front of a driving simulator. In the experiments, ECG signals and eye-blink video sequences were obtained for analysis; additionally, the test drivers' facial expressions were recorded for subjective drowsiness rating. Temporal resolution of the estimation of drowsiness level was set at ten seconds.

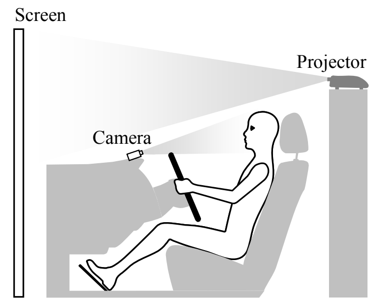

Fig. 3. Overview of a driving simulator.


Fig. 4. Driving simulator program.

B. Evaluation approach for each method

To evaluate the experimental results with each method, we used the *Accuracy* among the drowsiness level from facial expression and the estimated drowsiness level. Rating the facial expression was conducted by two examiners based on the video sequences recorded during the experiments. The expression defining the *Accuracy* is

$$Accuracy = \frac{\sum_{t=1}^{T} \sum_{i=1}^{n} [y_t^i \in H_t(x_t^i)]}{nT} \tag{10}$$

where t is the number of test sets, T is the maximum value of t. The notation n means the length of data, y_t means the correct label of test set t, and H_t means the hypothesis of test set t.

TABLE II
RESULTS OF ACCURACY WITH EACH METHOD

Method	*Accuracy* [%]
LDA	36.91
k-NN	41.37
HD-ECOC	60.69
LD-ECOC	88.78

C. Results

With extracting the mean value and variance value of RRI, SNA, PNA and the degree of eyelid closure for the input features of the binary classifiers, we estimated the driver's drowsiness level. In the estimation procedure, we adopted HD-ECOC and LD-ECOC for decoding and AdaBoost for binary classifiers. The results of accuracy with each method are shown in Table II. For purpose of comparison, Table II includes the results of estimation with Linear Discriminant Analysis (LDA)[13] and *k*-Nearest-Neighbors classification rule (*k*-NN)[14]. Figure 5 (top portion, thick line) shows a typical example of trend-chart of drowsiness levels, as

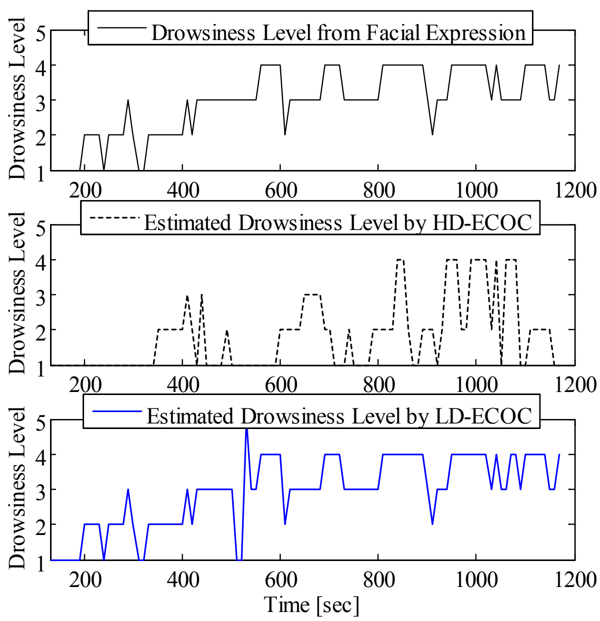

Fig. 5. Top, Drowsiness level from facial expressions; Middle, drowsiness level estimated by Hamming decoding ECOC; Bottom, drowsiness level estimated by the proposed Loss-based decoding ECOC

obtained from the facial expressions using human rater. It is being compared respectively with the drowsiness level estimated by the Hamming Decoding ECOC (Fig 5, middle, dashed line) and the proposed Loss based Decoding ECOC (Fig 5, bottom, colored line). Note that the colored line resembles the thick line with much higher accuracy as compared to that of the HD-ECOC.

V. CONCLUSION

This paper describes development of a novel method for estimation of the driver's drowsiness level based on eyelid closure and heart rate variability. We used Error-Correcting Output Coding (ECOC), which enables binary classifiers to classify at multiple levels for a low computation cost. The classification technique is proposed on the basis of class tendencies of each drowsiness level using a loss function for decoding procedure. Through the performance validation of proposed method during the experiments using the driving simulator, we obtained very high accuracy for estimating the drowsiness level. While Hamming Decoding ECOC method, concerned with either +1 or -1 only, yielded merely 60.69% accuracy, our proposed Loss-based decoding ECOC method obtained a much higher accuracy of 88.78% by taking into account the class tendencies. Comparison with other Neural Network based methods, raising the accuracy of estimation, and developing an way to estimate subject drowsiness level directly from the facial expression need future work.

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