# A Method to Detect Inappropriate Postures causing Distraction via Analysis of Pressure Distribution on the Driving Seat

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## Abstract

This paper proposes a method to identify driver's posture based on pressure distribution on the driving seat. In our method, the Higher-order Local Auto-Correlation (HLAC) features are extracted from an image of a pressure distribution. We conducted an experiment to investigate effectiveness of our method. The data were collected on a driving simulator. The results showed that the method is potentially useful for estimating driver's action. We tried to find ways to improve the performance of the method. The results show that using two sensor sheets on the seat cushion and the backrest is necessary. The resolution of a sensor sheet can be reduced to half of the original or less. If the training samples have lots of varieties, the mean recognition rate was up to approximately 85% suggesting the effectiveness of the detection method.

## 1. Introduction

In order to improve road traffic safety, it is one of vital issues to establish methods to modify the way of driver support depending on traffic conditions and driver's states (Inagaki, 2007). Development of methods for detecting driver distraction is thus important.

Design of methods for detecting driver distraction depends on types of distractions. Ranny, et al. (2000) distinguished four categories of distractions: “visual”, “auditory”, “biomechanical”, and “cognitive”.

“Visual distraction” stands for “looking aside.” There are lots of methods to detect “looking aside.” For example, Inayoshi and Kurita (2007) have developed a driver’s head pose identification method with a single camera. Moreover, several vehicles in Japan are equipped with a system which detects such distraction.

When a driver is performing a cognitive task which does not require driver’s motion (e.g., thinking about something serious issue), it is called that the driver is “cognitively distracted”. “Auditory distraction” refers to paying driver’s attention to hearing something (e.g., radio or music) too much other than driving. At least in some cases, the driver’s mental workload increases when the driver is in a cognitive or auditory distraction. Therefore, such distraction can be detected by a method for measuring mental workload. Facial temperature (e.g., see, Veltman, et al. (2005), eye movement (e.g., see Itoh and Inagaki (2008)), blood pulse wave (e.g., see, Suzuki and Okada (2008) are candidates for detecting high mental workload effectively and non-intrusively.

Biomechanical distraction stands for situation in which a driver is performing a task which requires driver’s motion, e.g., taking something to eat/drink. These kinds of activities can often be observed in automobiles including professional drivers (e.g., see, Barr, et al. (2003); Itoh & Yoshimura (2007)). Therefore, it is important to develop methods to detect biomechanical distractions. However, there are few researches on the detection of biomechanical distractions. One related study is done by Riener, et al. (2007). They suggest that pressure distribution on the driving seat might be useful for estimating driver's attentiveness to the driving. However, it has not been clarified how driver's posture can be identified based on the pressure distribution.

The authors have been working on development of driver biomechanical distraction

(Itoh, et al. (2007)). In Itoh, et al. (2007), the information on the load center position of the pressure distributions on the backrest was used to detect driver's body movement. The method was effective to detect movement but was not good enough to identify one action. This paper proposes a new approach to identify a posture by taking the pressure distribution itself into account.

## 2. Posture recognition method

This paper proposes to use HLAC (Higher-order Local AutoCorrelation) features (Otsu, Kurita, 1988) extracted from an "image" of the pressure distribution on the driving seat. HLAC features are often used for image recognition since HLAC features are inherently shift-invariant and computationally inexpensive (e.g., see, Kurita and Hayamizu (2003)). These characteristics of HLAC features suggest that the use of HLAC features may be suitable to detect a driver inappropriate posture in an automobile.

In this paper, pressure distribution sensors shown in Figure 1 are used. The sensor sheet on the seat cushion has 38 * 37 sensing points, and the sensor sheet on the backrest has 25 * 40 sensing points. Sample images of these sensors are shown in Figure 2.

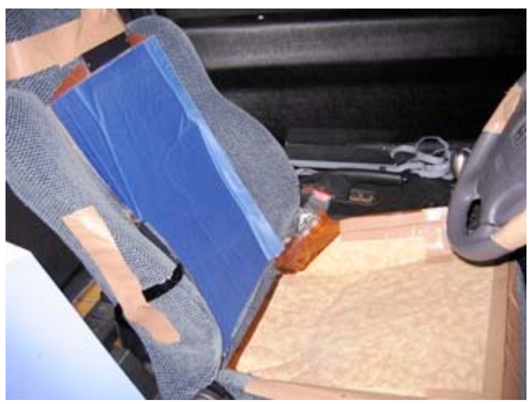

Figure 1 Pressure distribution sensors

From each figure, HLAC features are extracted. In general, N-th order autocorrelation functions with N displacements $\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_N$ are defined by

$$x(\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_N) = \int f(\mathbf{r}) f(\mathbf{r} + \mathbf{a}_1) \cdots f(\mathbf{r} + \mathbf{a}_N) d\mathbf{r},$$

where $f(\mathbf{r})$ denotes the pixel value at the reference point $\mathbf{r}$. The number of these autocorrelation functions is enormous. It is necessary to reduce it for practical image recognition. A typical way for this is to make restrictions as follows:

- the value of N is not greater than two (i.e., N=0,1,2),
- the range of displacements is within a local 3 * 3 window, where the center of which is the reference point.

This paper obeys the restrictions too. In this case, the number of patterns of displacements is reduced to 35 (an equivalent displacement to another one by the shift is eliminated). Figure 3 depicts the 35 mask patterns. By applying the masks to all pixels in an image, HLAC features are computed and a feature vector whose dimension is 35 is obtained.

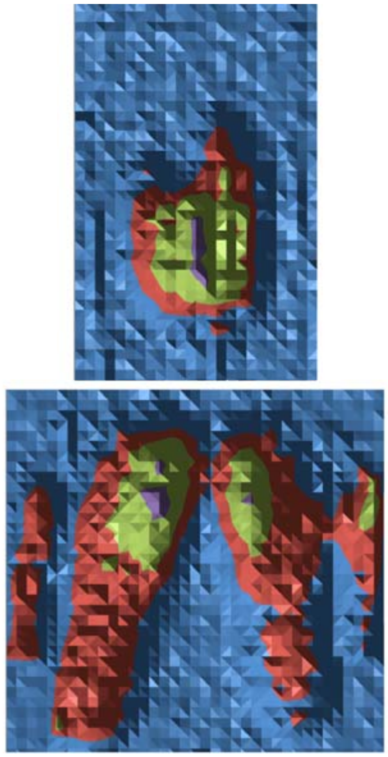

Figure 2 Sample images of the pressure distributions

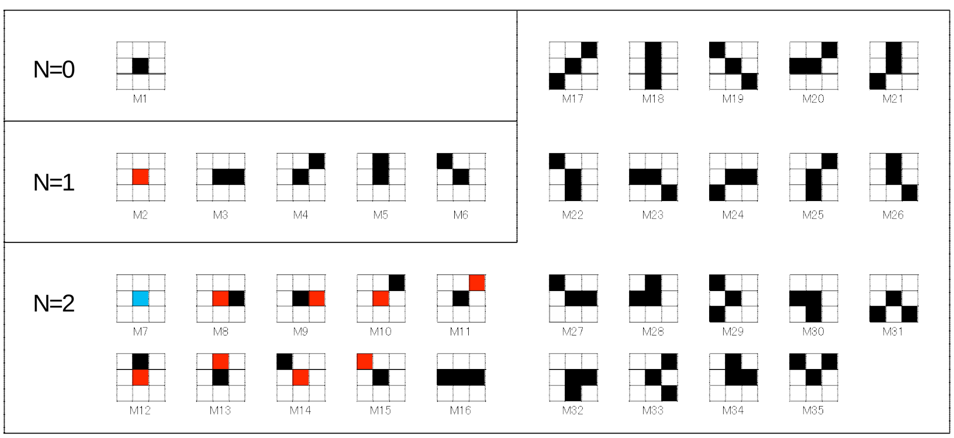


Figure 3 Local mask patterns for computing HLAC features

Each feature vector $\mathbf{x}$ is mapped to a new feature vector $\mathbf{y}$ in a discriminant space by Linear Discriminant Analysis (LDA). The new feature $\mathbf{y}$ is derived as

$$\mathbf{y} = \mathbf{A}^T \mathbf{x},$$

where $\mathbf{A} = [a_{ij}]$ is a coefficient matrix. The optimal coefficients can be determined from training samples so as to maximize a discriminant criterion $J = tr(\hat{\Sigma}_W^{-1}\hat{\Sigma}_B)$, where $\hat{\Sigma}_W$ and $\hat{\Sigma}_B$ denote the within-class and between-class covariance matrices defined on $\mathbf{y}$. The optimal coefficient matrix $\mathbf{A}$ which maximizes $J$ is obtained by solving the eigenvalue problem

$$\Sigma_B \mathbf{A} = \Sigma_W \mathbf{A}\Lambda \ \ (\mathbf{A}^T \Sigma_W \mathbf{A} = \mathbf{I}),$$

where $\Sigma_W$ and $\Sigma_B$ are the within-class and between-class covariance matrices defined on $\mathbf{x}$, and $\Lambda$ is the diagonal matrix of the eigenvalues.

In this paper, a simple classifier is used to identify the class of the posture. The classifier checks the distance from an input vector $\mathbf{y}$ derived from a test sample to the mean vector $\bar{\mathbf{y}}_k$ of Class $k$ in the discriminant space. The input is classified to the nearest class.

## 3. Experiment

### 3.1 Purpose

The purpose of the experiment is to find a reliable and cost-effective way to realize the detection system. The following factors may be related to the reliability of the detection and the cost.

(1) The number of the sensor sheets. If either the sensor sheet on the seat cushion or the sheet on the backrest is enough, the other one can be removed.

(2) The resolution of the sensor sheets. If both sensor sheets are required, one way to reduce the cost is to reduce the number of sensing points on a sensor sheet. Reduction of the resolution might contribute to improvement of the reliability. The extracted HLAC features may not be appropriate if the resolution is too high, since HLAC features are extracted from only the very local areas (as stated above, a 3 * 3 local window is usually used).

(3) Varieties of training samples. If the training samples contain wide varieties in the data, the detection system may be robust. However, increasing of the varieties may raise the cost.

(4) Individualization. If the detection system is individualized, the system may be reliable but expensive. If the individualization is not necessary, we can also reduce the cost of the detection system.

### 3.2 Method

Ten persons (five females (aged from 23-38) and five males (aged from 22-39) participated in the experiment. Even though the participants were recruited through a temporary staffing agency, they were given the same rights as the ordinal voluntary participants. The participants were paid according to the guideline at the University of Tsukuba.

The data were collected on a driving simulator shown in Figure 4. The driving simulator is motion-based. However, the motion was not provided in this experiment. The participants were not asked to drive the vehicle. Their task was just to take a posture on the driving seat. Five classes are distinguished in this experiment as follows:

C1. Take the normal driving posture.

C2. Reach the left hand to the left as far as possible (Figure 5 (C2)). This aims to simulate picking up something on the passenger seat next to the driving seat (note here that the driving seat is on the right hand side in Japan).

C3. Touch a point as shown in Figure 5 (C3). This aims to simulate taking something in the pocket on the back of the passenger seat.

C4. Touch a navigation screen which is located at the center of the dashboard (Figure 5(C4)).

C5. With the right hand, touch the floor as shown in Figure 5(C5). The point to touch is near the right heel.

For each posture, a driver is asked to press a gas pedal a little. The position of the driving seat and the angle of the backrest were set as a participant feels comfort. At the first stage of the experiment, those parameters are recorded. Before starting each data collection, the driving seat was configured based on the parameter values. Every driver was also asked to fasten the seatbelt.

Two types (type-A and type-B) of samples are collected for this experiment. For type-A samples, a participant is asked to take a posture only once from C1 to C5. For each posture, 100 snapshots are taken at one time for a data set. This way of taking data is time-saving, but the data in the same class may be similar to one another. For type-B samples, a participant is asked to take a posture twenty times from C2 to C5. The order is randomized. Between each pair of postures, a participant is asked to come back to C1 (Thus, C1 was taken 80 times). At each posture taking, five snapshots are recorded. Thus, we have 100 snapshots for each class (for C1, 100 snapshots are randomly chosen) as a data set. This way of taking data is time-consuming, but the data may have wide varieties.

Figure 4 The driving simulator

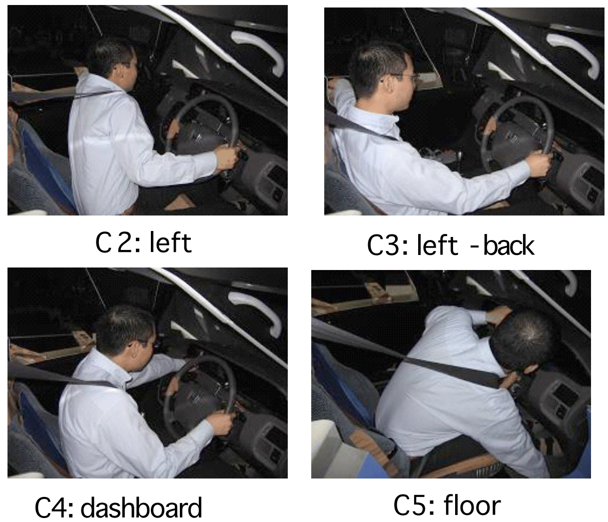


Figure 5 Secondary actions

The data collection lasted three days for each participant. In each day, one type-A data set and three type-B data sets are recorded. After completion of one data set recording, every participant gets off the driving simulator and takes some rests. Thus, the initial driving positions differ from one another slightly.

## 3. Results and Discussions

First, the necessity of both sensor sheets is discussed. Three conditions, i.e., using only the sensor on the seat cushion, using only the sensor on the backrest, and both, are compared. By calculating the (correct) recognition rate for each participant, the data shown in Figure 6 was obtained (each error bar represents the standard deviation of the associated condition). In this analysis, training is based on a type-A data set. All (nine) the type-B data sets are tested to each training data set. Therefore, 27 tests are done for each participant. The recognition rate of a participant used in Figure 6 is a mean recognition rate of the 27 tests.

We conducted a single-factor repeated measures ANOVA on the recognition rate. The main effect was statistically significant ($F(2, 18)=12.53$, $p<0.0004$). Tukey's HSD test revealed that there were significant differences between "both" condition and "seat cushion only" condition ($p<0.01$), and between "both" condition and "backrest" condition ($p<0.01$). Therefore, using the two sensor sheets are necessary for achieving high recognition rate.

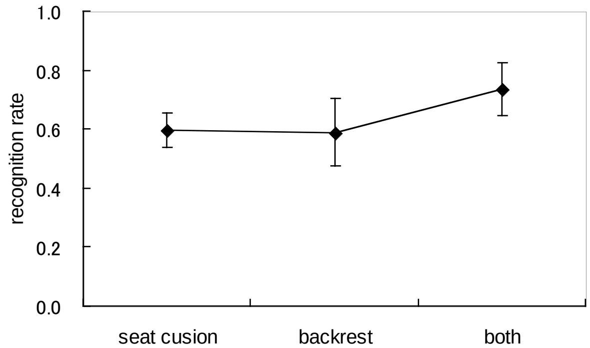


Figure 6 Effect of combining the sensor sheets on recognition rate

Second, reduction of the sensor resolution is discussed. Using the two sensor sheets may result in increase of the cost. It is necessary for us to find a way to reduce the cost. One possible way is to reduce the number of sensing points on a sheet. Figure 7 depicts the result of the reducing the resolution. The horizontal axis represents the reduction rate of the resolution. The vertical axis represents the difference in the mean recognition rates between the tests based on the original data and a test based on the resolution-reduced data. According to Figure 7, the resolution reduction does not decrease the recognition rate at least the resolution equals to or is greater than 1/8 of the original one for the "both" condition. This result implies that the total number of sensing points can be reduced from the original setting even if the two sensor sheets are used.

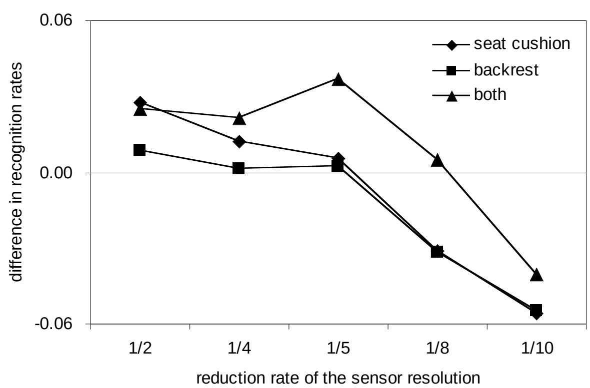


Figure 7 Effect of reducing resolution on detection rate

Third, we discuss increasing of variety of training samples. There is a room to improve the recognition rate even when the two sensor sheets are used. Here, we investigate effectiveness of increasing variety of training samples. Four types of trainings are compared. In each type, training is done with

Type-1: a single type-A data set,
Type-2: a single type-B data set,
Type-3: a mixture of two type-B data sets in one day,
Type-4: a mixture of two type-B data sets that are from different days from each other.

In types-3 and 4, the number of training samples for each class is kept at 100 by extracting samples randomly. For every type of training, tests are done with the remaining type-B data sets. The total recognition rate for each type is calculated as the mean recognition rate of the all tests in the type. In Figure 8, the mean value of the all participants' total recognition rates is shown for each type. The error bars represent the standard deviations. A single-factor repeated-measures ANOVA showed that the main effect of training type was statistically significant ($F(3, 27)=19.99$, $p<0.01$). According to Tukey's HSD test, there were significant or nearly significant differences between type-1 and type-2 ($p=0.08$), between type-1 and type-3 ($p=0.0005$), between type-1 and type-4 ($p=0.0002$), between type-2 and type-4 ($p=0.0004$), and between type-3 and type-4 ($p=0.06$). Thus, it can be claimed that the higher the variety in training samples, the higher the recognition rate.

In our experiment, the final recognition rate was approximately 85% as shown in Figure 8 (type-4). Even though this is not high enough for practical use, the result suggests that our proposed method is potentially useful. Detection rate depends on combination of classes to be categorized. For example, as shown in Figure 9, the recognition rate for C3 was relatively low for both training types 1 and 4. This result suggests that the recognition rate can be higher if we can neglect C3. Whether C3 can be neglected or not depends on the purpose of the detection system. Since body movement in C3 is small, driving maneuver may not be significantly degraded. If the system aims to hit the automatic brake when a rear-end collision is imminent, for example, the system does not need to detect actions like C3. If the system aims to give some caution when a driver is paying his or her attention to something other than driving itself, however, the system has to detect such actions. The reliability of the detection required to the system is also dependent on the severity of the situation and/or degree of support.

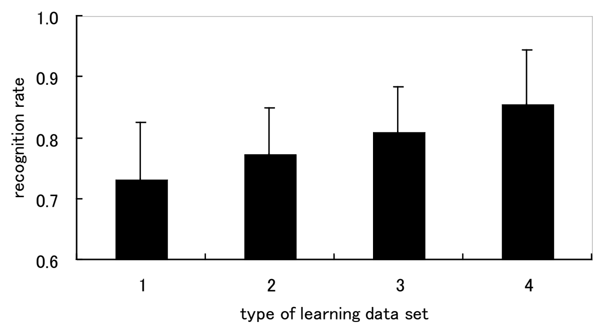


Figure 8 Dependence of recognition rate on learning data

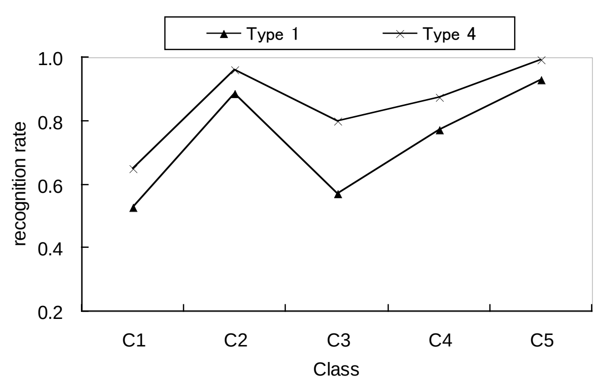


Figure 9 Difference between types 1 and 4 in recognition rate for each class

Finally, necessity of individualization for training is discussed. In the above analyses, training was done separately for each participant. Here, the following two types of training are taken into account. In each type, training is done with

Type-5: randomly chosen 100 samples for each class from all the type-B data sets of all participants,

Type-6: randomly chosen 100 samples for each class from all the type-B data sets of nine participants other than the tested person.

For tests based on type-5 trainings, 10% of the training samples are from the own data of the tested person. On the other hand, no own data are included in the type-6 samples for each person. Tests are with the remaining type-B samples for each participant.

Figure 10 shows the differences among training types 4, 5, and 6 by showing each participant's recognition rates of those types. A single-factor repeated-measures ANOVA for these data showed that the main effect of the training was significant ($F(2, 18)=15.7$, $p<0.01$). According to Tukey's HSD test, there was no significant difference between type-4 and type-5. However, there were statistically significant differences between type-4 and type 5 ($p<0.01$), and between type-5 and type-6 ($p<0.01$). The results show that training based on a "common" data set can be almost the same as the one based on the individualized training data set if at least 10% of the "common" data is from the own data of the tested person. However, if the training samples do not have the data of the tested person at all, the recognition was degraded. The result implies that common training can be done if we can categorize drivers into small number of groups, where differences among drivers in the same group can be neglected from the view point of the pressure distributions.

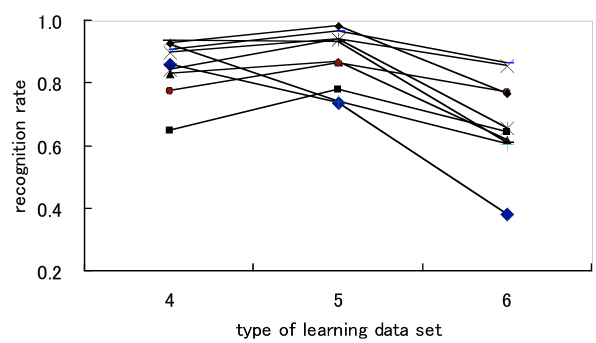


Figure 10 Effect of including driver's own data in learning data set

## 4. Concluding Remarks

We have proposed to apply an image recognition technique for identification of driver posture from several alternatives. Since our method extracts HLAC features from the pressure distributions on the driving seat, the method is shift-invariant and computationally inexpensive.

The results of the experiment showed that both the sensor sheets on the seat cushion and the backrest are necessary, but the cost can be saved since the sensing points can be reduced to the half of the original or less. In order to achieve robust recognition, wide variety of training samples is needed. However, the cost of collection training samples may not be so high, since our results suggest that individual training may not be necessary if we can categorize drivers into small number of groups.

Further research would be needed to investigate whether our approach is robust or not when a vehicle is running. Careful design of supports to a driver based on this monitoring should also be established.

As Itoh (2008) pointed out, pressure distributions on the driving seat is useful not only for detecting driver's biomechanical distraction but also other objectives. For example, our method proposed in this paper can also be applied to evaluate driver's situation awareness. That is, our method can be used to detect that a driver is ready to hit the brake (Itoh, et al., 2008). Riener and Ferscha (2008) tried to develop a person identification method based on the pressure distribution information. Detecting driver's fatigue (e.g., see, Furugori, et al. (2005)) and drowsiness (e.g., see, Kaneko, et al. (2008)) can also be done by analyzing pressure information on the driving seat. Integrating these methods will be vital for the future safety support systems.

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