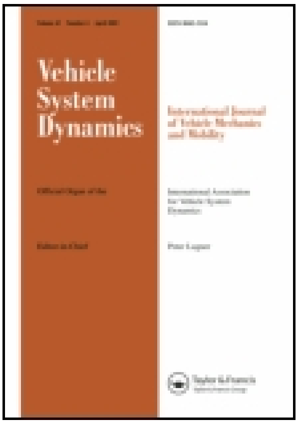

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Integrated driver modelling considering state transition feature for individual adaptation of driver assistance systems

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This paper describes the modelling of naturalistic driving behaviour in real-world traffic scenarios, based on driving data collected via an experimental automobile equipped with a continuous sensing drive recorder. This paper focuses on the longitudinal driving situations which are classified into five categories – car following, braking, free following, decelerating and stopping – and are referred to as driving states. Here, the model is assumed to be represented by a state flow diagram. Statistical machine learning of driver–vehicle–environment system model based on driving database is conducted by a discriminative modelling approach called boosting sequential labelling method.

Keywords: driver assistance systems; driver behaviour; individual adaptation; naturalistic driving; statistical machine learning

1. Introduction

Focusing on today's active safety devices, a number of driving assistance systems have been developed for many years and some of them are equipped in vehicles on the market. The design of human–machine interface (HMI) for driver assistance systems to obtain the satisfactory interaction in cooperative manoeuvre between safety system and human driver manual control has become a major issue of the driver assistance system study. Practical cooperative control systems between drivers and driver assistance systems that fit driver behaviour/intention and traffic condition imply a need for practical driver–vehicle–environment model. Past research works by the authors give the understanding that it is important to utilise driving data in real-world traffic situation to make the HMI of ADAS more effective and acceptable for large-scale customers [1,2]. The predetermined driving route for data collection in this research is purposefully regarded as the driver's commuting path in order to examine their driving

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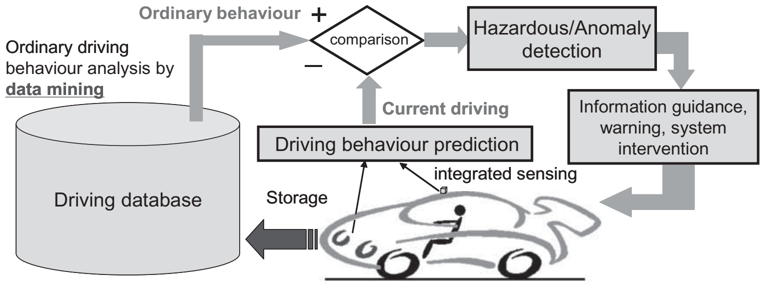

Figure 1. Conceptual diagram of individual adaptation algorithm.

behaviour. Figure 1 shows the schematic diagram of the personalised driver assistance system. The technology requirements of this system are as follows:

- *Driving data recording technology* with an extended-functionality drive recorder,
- *Individual adaptation technology* for modelling driver behaviour and extracting individual driving characteristics,
- *Risk assessment technology* for evaluating the hazardous potential,
- *HMI technology* for the practical design of driver assistance system.

The main goal of the individual adaptation of driver assistance system is to provide information, give the driver warning, or manoeuvre guidance/intervention in necessary situations adapted to the driving environment and individual driver, as shown in Figure 2. The system is required to recognise the risk potential of the driving environment and the driver attention in driving to judge the risk of accidents and necessity of the driver assistance system in real time. Since rear-end collision accounts for about 30% of all road accidents in Japan and other countries, in the beginning phase of our research, we focus on developing a driving behaviour recognition framework in longitudinal driving manoeuvres which is one of the core technologies of individual adaptation technique. This paper describes the analysis of the naturalistic driving behaviour in real-world traffic situations, based on driving data collected through the experimental vehicle equipped with a drive recorder in order to synthesise a driver–vehicle–environment model in urban area driving.

Many driver behaviour models for automotive applications have been studied for many years as summarised in Ploechl's state-of-the-art paper [3]. Most of them are focused on the limited driving situations such as car-following, lane-keeping, etc. This paper focuses on a combined driver behaviour model considering state transition feature – for example, from the

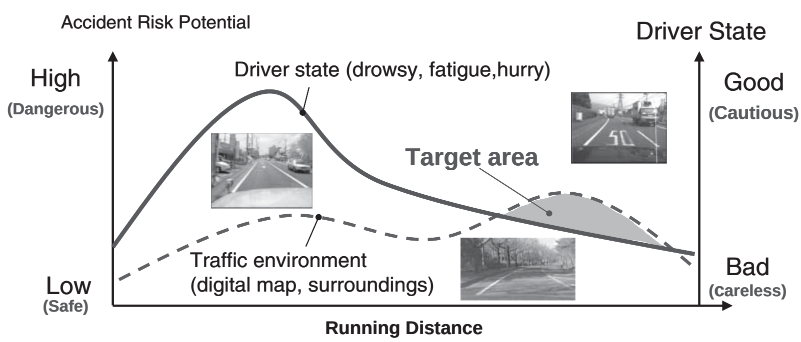

Figure 2. Target of the individual adaptive driver assistance systems.

car-following state to the free-cruising state, or from the car-following state to the braking state. Understanding the driver behaviour in such driving state transition leads to the design of driver assistance systems in the region that the hazardous potential is not high, e.g. to detect unusual driving behaviour of a driver. There has been a large body of literature relevant to driver assistance systems and driving behaviour learning [4–10]. Liu and Pentland [4] and Liu and Salvucci [5] used Hidden Markov Model (HMM) to recognise driver intentions in turning manoeuvres and lane change manoeuvres. Kuge *et al.* [6] applied Hidden Markov Model to recognise lane keeping and lane change manoeuvres based on the steering angle data from driving simulator experiments. Amano *et al.* [7] used Bayesian Network (BN) to predict the starting manoeuvre at intersections in a driver support system which prevents unsafe confirmation for reducing the traffic accidents during the intersection. Kumagai *et al.* makes use of a dynamic BN and the junction tree algorithm for probabilistic inference to predict the stopping behaviour at an intersection. The prediction algorithm could be used for warning and braking assist systems to prevent dangerous actions, such as red-light violations, by allowing detection of a deviation from normal behaviour [8]. McCall and Trivedi [9] introduced a method based on Bayesian probabilistic theory to predict the braking behaviour of driver with the information of driver behaviour (driver's head and feet), vehicle and surroundings for braking assistance. Gerdes [10] presented an automatic manoeuvre-recognition system based on a Bayesian model to classify driving behaviour in urban area such as left turn, right turn, car following, lane following, lane change, etc. In some of these works, ongoing driver's manoeuvres are commonly categorised into mutually exclusive classes, which, in this research, shall be called *driving states*. Definitions of these driving states are based on driver's operations and traffic environment. In order to recognise the driving behaviour, our objective is to develop a classifier that can recognise the driving states efficiently using the data on vehicle motions and environment.

As the driving-state-recognition problem involves many features, it is preferable to adopt non-generative models like maximum entropy Markov models (MEMMs) or conditional random fields (CRFs) [11,12]. Here, we employ the boosting sequential labelling method (BSLM) [13], whose concept is partially based on the CRFs framework, which has been proved to be superior to MEMMs [11].

In the next section, the designated driving course and collection of the experimental data are described. In Section 3, a recognition problem of the driving behaviour is formulated. The definitions of the driving states, a driving behaviour model, and a short overview on the

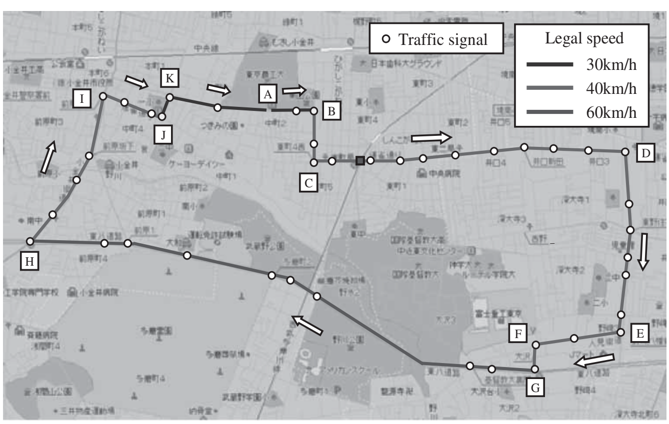

Figure 3. Driving route for data collection in Tokyo urban area.

framework of BSLM and its application to our problem are presented. Then, the computational results of the driving state recognition are given and discussed in Section 4. Then, an example of driver behaviour modelling based on driving state transition is demonstrated in Section 5. Finally, we state the concluding remarks and perspectives in the last section.

2. Real-world driving data collection using drive recorder

The selected driving course in this research is depicted in Figure 3 including several types of roadways in Tokyo urban area. In the experiment to be described later, driving data on two roadways are collected. The roadways are named as R1 and R2. From Figure 3, R1 is the $\overline{CD}$ section, whose distance is about 2 km, and R2 is the $\overline{\mathbf{GH}}$ section, whose distance is about 3.5 km.

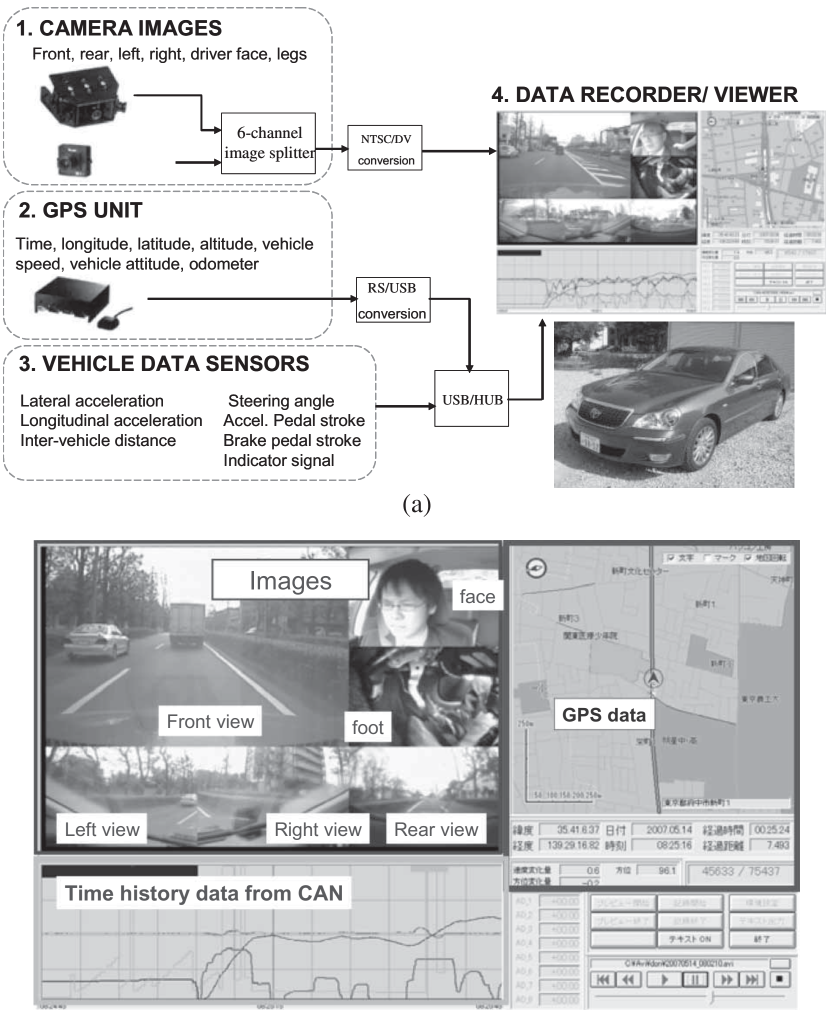

Figure 4. Configuration of the continuous sensing drive recorder in the test vehicle. (a) Configuration of sensors and video recording system and (b) Data acquisition system.

The experimental vehicle is equipped with a continuous sensing drive recorder, comprising vehicle sensors and instruments for data capture as vehicle speed sensors, an accelerometer, a gyro sensor, a GPS antenna, a millimetre wave radar, on-vehicle CCD cameras and a multi-view image synthesiser system. By means of these devices, driving data (e.g. speed, acceleration, yaw rate, vehicle position, headway distance) and videos showing ongoing operations of the driver (e.g. steering, pedal manoeuvres, gaze direction) and surroundings can be used in the subsequent driving behaviour analysis. The video images of front scenery, rear scenery, driver's face and driver's foot operation are captured in synchronisation with the sensor data. The configuration of the continuous sensing drive recorder is shown in Figure 4.

As the first step of the study on advanced driver assistance systems design with individual adaptation, driving behaviour regarding longitudinal vehicle dynamics, i.e. accelerating and braking, is mainly focused. Hence, measured driving data of which we make use in this work includes the following items:

(1) R: headway distance (m).
(2) $\dot{R}$: relative velocity, i.e. derivative of R (m/s).
(3) V: host vehicle velocity (km/h).
(4) a_x: longitudinal acceleration (m/s^2).
(5) X: GPS longitudinal coordinate (°).
(6) Y: GPS latitudinal coordinate (°).

The measurement sampling frequency is 30 Hz. In addition, the time headway T_{hw} – defined as the headway distance divided by the host vehicle velocity – and the inverse of time to collision T_{tc}^{-1} – defined as the headway distance divided by the relative velocity – are also employed in the driving behaviour analysis.

3. Framework of driver–vehicle–environment modelling

The longitudinal driving behaviour is categorised into five states: following, braking, cruising, decelerating and stopping states. Here, five symbols are labelled to these states as F, B, C, D and S, respectively. These driving states are defined as follows:

(1) Following state (F): There exists a preceding vehicle and either the driver is approaching the preceding vehicle or the driver intends to maintain R by hitting the acceleration pedal or hitting no pedal at all.
(2) Braking state (B): There exists a preceding vehicle and the driver slows down the host vehicle by hitting the brake pedal.
(3) Cruising state (C): The preceding vehicle is absent or is so distant that the driver does not intend to pursue, and thus, cruises with desired speed by hitting the acceleration pedal or hitting no pedal at all.
(4) Decelerating state (D): The conditions are the same as in C state except that the driver hits the brake pedal just as in the case that the driver wants to stop at traffic light as well as stop line located in an intersection.
(5) Stopping state (S): The host vehicle is not moving.

Illustrations associated to these states are shown in Figure 4. From the viewpoint of active safety, there exists a driver assistance application which relates to each driving state. For example, F corresponds to *adaptive cruise control* system; B corresponds to *forward collision avoidance/warning* system; C corresponds to *intelligent speed adaptation*; D corresponds

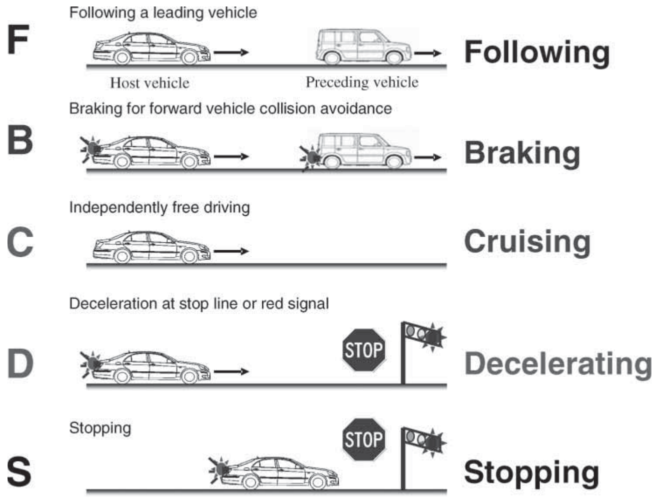

Figure 5. Definition of each driving state.

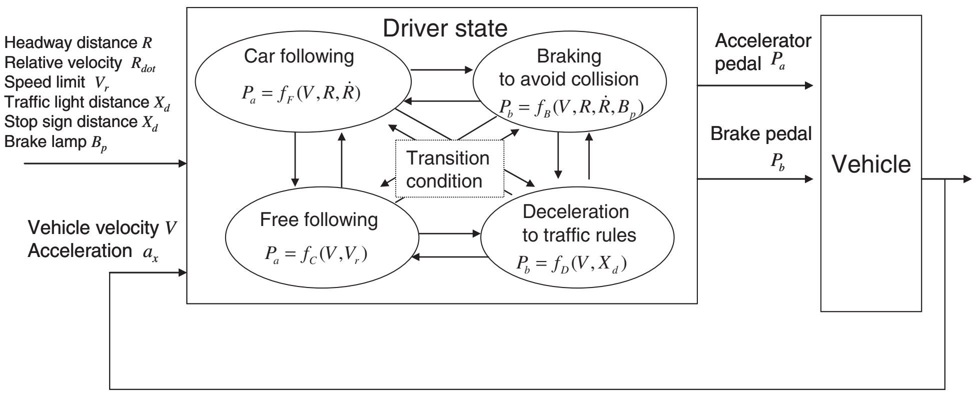

Figure 6. State flow diagram of driver model in longitudinal driver–vehicle dynamics.

to intersection stop assistance as well as intersection assistance when approaching a red traffic light.

The driver model is assumed to be described by the *state flow diagram* composed of possible transitions between states and their probabilities as shown in Figure 5. Here, we propose the driver–vehicle–environment model as shown in Figure 6.

To train the driver–vehicle–environment model for driving behaviour recognition, BSLM has been employed to calculate the conditional probability that describes the relationship between the sensor data of the drive recorder and the driving states. The concept of the BSLM framework is roughly demonstrated in Figure 7. From the model synthesised by a statistical data-driven method as indicated in Figure 8, the driving state annotation, i.e. labelling, is conducted by discriminative approach which is based on the current observation data (from vehicle sensors) and the previous driving state (recognised result).

BSLM is based on statistical machine learning that synthesises the model of driver–vehicle–environment for real-time driving state recognition. The conditional probability of driving state

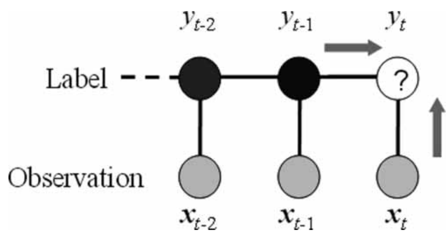

Figure 7. Schematic view of sequential label estimation algorithm.

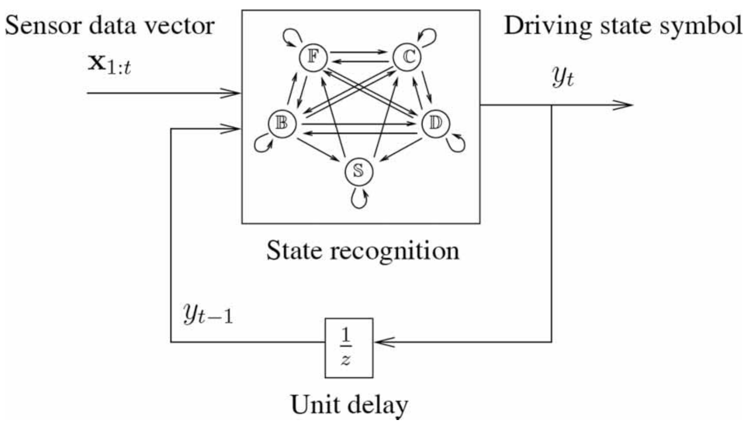

Figure 8. Interpretation of the BSLM framework in driving-state recognition.

based on sensor data can be expressed as a recurrence relation as follows:

$$p(y_t|x_{1:t}) \propto \exp\left(F_{yt}(x_t) + \left\langle G_{yt}(y_{t-1})\right\rangle_{\tilde{p}(y_{t-1})}\right) \tag{1}$$

where

$$\tilde{p}(y_{t-1}) = p(y_{t-1}|\boldsymbol{x}_{1:t-1}) \tag{2}$$

and the sign $\langle\cdot\rangle$ stands for the expectation value, y_t is the driving-state label at time t as follows:

$$y_t \in \{F, B, C, D, S\} \tag{3}$$

and $\boldsymbol{x}_{1:t}$ is the sensor data sequence from the initial time 1 to arbitrary time t. Here, $\boldsymbol{x}$ is the vector consisting of sensor data obtained from the drive recorder

$$x(t) = \begin{bmatrix} R(t) & \dot{R}(t) & V(t) & \dot{V}(t) & X(t) & Y(t) \end{bmatrix}^T. \tag{4}$$

The discriminative function F_{yt} in Equation (1) defines the consistency of the combination between the sensor data $\boldsymbol{x}$ and the driving-state label y at the time stamp t, while the discriminative function G_{yt} defines the dependency of current driving state with respect to that of the previous time stamp $t-1$. Both functions are obtained via boosting method by updating the discriminative functions with the weak learners f_{yt} and g_{yt} as

$$F_{yt} \leftarrow F_{yt} + v f_{yt} \tag{5}$$

$$G_{yt} \leftarrow G_{yt} + v g_{yt} \tag{6}$$

for the prescribed number of iterations. The parameter v is between zero and one and is adjustable. In this work, the form of the weak learners are formulated as follows:

$$f_{yt}(x_t) = \begin{cases} \alpha_{yt}, & \text{if} \quad x_t(i) > \theta \\ \alpha'_{yt}, & \text{if} \quad x_t(i) \leq \theta \end{cases} \tag{7}$$

and

$$g_{yt}(y_{t-1}) = \frac{\sum_t w_{t,yt} z_{t,yt} \tilde{p}(y_{t-1})}{\sum_t w_{t,yt} \tilde{p}(y_{t-1})} \tag{8}$$

where $x_t(i)$ is the ith element of x_t. Let H be the Heaviside step function, which is defined as

$$H(x) = \begin{cases} 0, & \text{if} \quad x \leq 0 \\ 1, & \text{if} \quad x > 0. \end{cases} \tag{9}$$

The parameters α_{yt} and α'_{yt} in Equation (7) are computed as the following expressions:

$$\alpha_{yt} = \frac{\sum_t w_{t,yt} z_{t,yt} H(x_t(i) - \theta)}{\sum_t w_{t,yt} H(x_t(i) - \theta)} \tag{10}$$

$$\alpha'_{yt} = \frac{\sum_t w_{t,yt} z_{t,yt} (1 - H(x_t(i) - \theta))}{\sum_t w_{t,yt} (1 - H(x_t(i) - \theta))} \tag{11}$$

by seeking for θ (e.g. binary search) and varying the index ith to minimise the following function.

$$\sum_t w_{t,yt} (f_{yt}(x_t) - z_{t,yt})^2 \tag{12}$$

The discriminative function F_{yt} and G_{yt} can also be interpreted as a set of a number of if-then rules (the set of weak learners f_{yt}), called *decision stumps*, which is shown in Figure 9. The decision stump is described by the parameters α_{yt}, α'_{yt} and θ in Equations (10) and (11). The

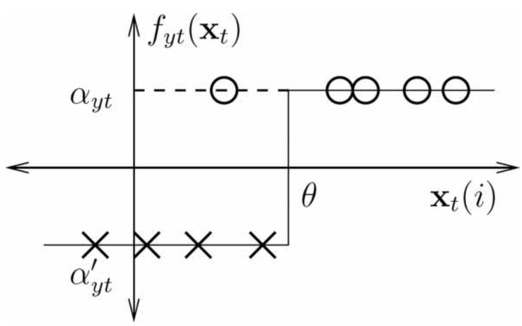

Figure 9. Decision stump defined by an if-then rule for state classification.
Note: The horizontal axis represents sensor data, and the vertical axis represents the weak learner f_{yt}. For a particular symbol, the circles are related to the values of $\mathbf{x}_t(i)$ where the values of y_t equal this symbol, while the cross marks are related to the values of $\mathbf{x}_t(i)$ where the values of y_t do not equal this symbol. The parameter θ is then obtained by fitting $f_{yt}(\mathbf{x}_t)$ to the data $\mathbf{x}_t(i)$.

decision stump is, accordingly, obtained by finding the parameter θ that fits $f_{yt}(\mathbf{x}_t)$ to the data points of $\mathbf{x}_t(i)$. The expression (1) is originally based on the idea of logistic regression model. In short, starting from $F_{yt} = 0$ and $G_{yt} = 0$, we compute $\hat{p}(y_t)$ at each t to obtain $w_{t,yt}$ and $z_{t,yt}$ and $g_{yt}(y_{t-1})$. These are then used to find the optimal $f_{yt}(x_t)$, which is, in turn, used to update F_{yt} and G_{yt} in the next iteration.

4. Driving state recognition results

To examine the recognition accuracy, the computed conditional probability $p(y|\mathbf{x})$ pertaining to the trained model is used to estimate a state sequence when the actual human-labelled state sequence is known, which is called *ground truth*. The estimated state sequence is then compared with the ground truth at each instant, and the accuracy of each state are computed. In so doing, driving data from three subject drivers on two different roadways are collected. The drivers' age range is from 23 to 28 years old, with driving experience of 3 to 10 years. We name the subject drivers as S1, S2 and S3, and the roadways as R1 and R2. For each driver on each roadway, eight sets of data (one set is associated to one trip of driving) are collected and labelled. Among these data sets, seven of them form a training data set; the left one is the validation data set.

We evaluate the estimation accuracy using a measure called F-measure, which is a harmonic mean of two other measures called precision and recall. The definition of F-measure is shown as the following expression:

$$F\text{-measure} = \frac{2(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \times 100\% \tag{13}$$

where, the precision and the recall indices are defined as follows:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \times 100\% \tag{14}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100\%. \tag{15}$$

Therefore, F-measure index is inverse-proportional to the summation of false positive and false negative. Larger summation of false values results in low value of F-measure, expressing the accuracy of the driving state recognition algorithm.

4.1. *Recognition results by exclusive learning of specific conditions*

First, we consider the cases when S1 driving on R1 and R2. Figures 10 and 11, respectively, show the driving state recognition results in road section R1 and R2 based on the proposed framework with time histories of sensor data obtained from the drive recorder.

As parts of the results, we also obtained the discriminative function F, appears in Equation (1), for each state, which can be used to interpret relationships between the measured data items and the driving states. The following facts were observed. Firstly, F depends much on almost every measured parameters except Y; it depends strongly on a_x and T_{hw}. B mainly depends on a_x and somewhat depends on V. C mainly depends on R and somewhat depends on a_x. In contrast, D mainly depends on a_x but somewhat depends on R and X. Finally, S almost entirely depends on V. We observed that no state has a strong relationship with Y, which is perhaps because both R1 and R2 roughly extend in latitudinal direction, and so Y does not vary much in all driving states.

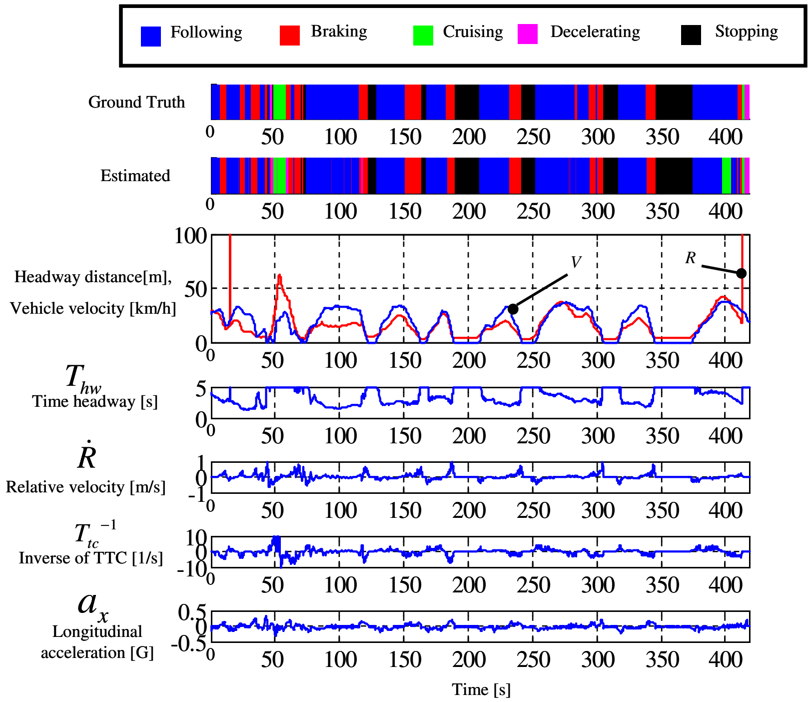

Figure 10. Driving state recognition result of driver S1 on road section R1.

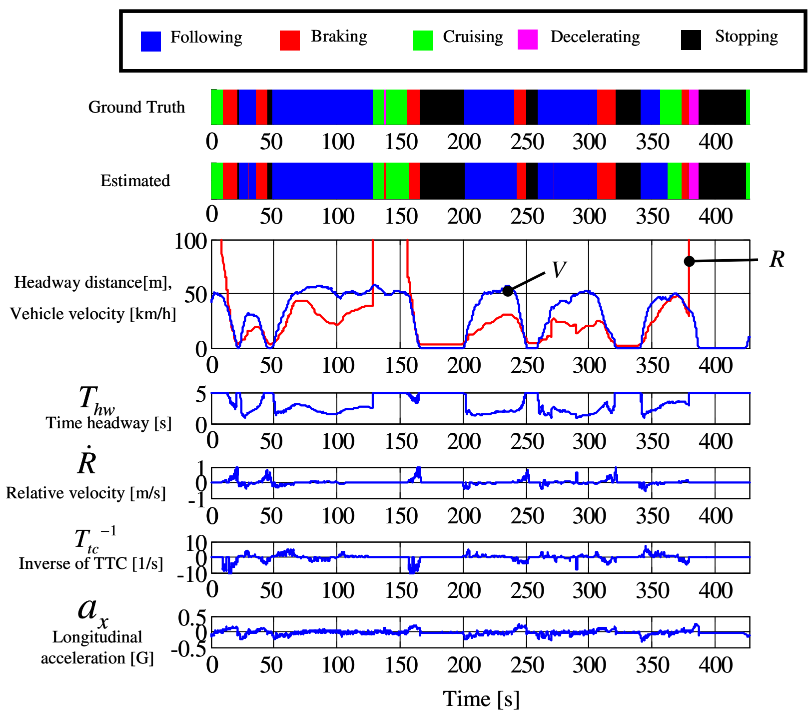

Figure 11. Driving state recognition result of driver S1 on road section R2.

Table 1. The F-measures of the exclusive validations associated with each driver on each roadway.

	F-measure (%)					
	R1			R2		
States	S1	S2	S3	S1	S2	S3
$\mathbb{F}$	96.6	90.2	90.3	98.2	97.3	97.3
$\mathbb{B}$	68.5	75.9	70.1	91.7	91.5	90.0
$\mathbb{C}$	96.5	92.1	94.8	96.1	96.9	93.0
$\mathbb{D}$	87.8	51.8	73.5	89.0	86.2	73.8
$\mathbb{S}$	100.0	100.0	100.0	100.0	100.0	100.0

Next, the estimation accuracies, evaluated by F-measure, are presented for the cases of exclusive recognitions, i.e. both training and validation data sets are from the same driver on the same roadway. The results are summarised in Table 1.

From this table, estimation of the stopping state S has no mistake. Estimation of the car-following state F and the cruising state C are relatively accurate when compared with the braking state B and decelerating state D. The accuracies of the decelerating state D are relatively low since it is generally difficult to estimate with currently available measured data. For instance, D occurs when the driver wants to stop at traffic lights or slow down the vehicle before entering a curved roadway; however, with no knowledge of the timing of traffic signals along road or real-time curvature detection, the prediction of the driver braking behaviour corresponding to the state D results in low accuracy. On the other hand, estimating the braking state B can be relatively easier than the state D since the classifier can observe the value of the headway distance and the time-to-collision, which strongly relates to the brake pedal operation. Furthermore, since there are more traffic lights on roadway R1 than R2, the driving behaviour is more varying on R1, which further reduces the accuracy of the B and D state estimations on R1.

4.2. *Recognition results by cross validation*

Next, the results pertaining to dependencies on the subject drivers and the local roadways are presented. We perform cross validations by varying the training data sets differently. First, we display the results when the roadway is fixed and the training data from the respective subject drivers are used. The recognition F-measure of each driving state is shown in Table 2. The recognition of S is omitted, as the F-measures in all cases are 100%. Next, we present the results when the subject driver is fixed and the training data from the respective road sections are used. For each state, the accuracy of recognition results evaluated by F-measure is summarised in Table 3.

From these tables, it can be noticed that when the training data sets changes, B and D recognition accuracies deviate significantly. This suggests that the accuracies in recognising B and D strongly depend on sources of data that is used to train the classifier. In nature, these two states are difficult to achieve satisfactory recognition results even by the exclusively trained classifier. Thus, accuracies of the recognitions using the classifiers trained by the different drivers or roads are even more degraded. On the contrary, overall recognitions of F and C (and certainly S) by different classifiers are satisfactory. This supports the viability of cross recognitions of F, C and S between different settings.

In future, further improvement in driving behaviour recognition for braking situation, i.e. braking and decelerating states (B and D), will be conducted. More information regarding road environment features and vehicles in the vicinity will be included.

Table 2. The F-measures of recognition results using classifiers trained by data sets from the same road section.

		F-measures (%)							
		Training data on R1				Training data on R2			
		S1	S2	S3	S123	S1	S2	S3	S123
𝔽									
Estim. data	S1	96.7	97.5	95.8	97.6	98.3	96.7	95.7	97.5
	S2	89.9	90.2	90.2	91.6	97.5	97.3	96.9	97.7
	S3	89.3	91.3	90.3	90.3	96.3	97.5	97.3	97.8
𝔹									
Estim. data	S1	68.5	87.1	60.2	70.8	91.7	90.1	84.6	90.7
	S2	70.2	76	73.7	73.7	89.4	91.5	90.2	91.6
	S3	63.3	76	70.1	70.3	91.2	90.8	90	91.1
ℂ									
Estim. data	S1	96.5	94.9	93.9	95.7	96.1	92.8	94.8	94.9
	S2	93.9	92.1	92	94.1	89	78.6	91.1	90
	S3	90.9	88.4	94.8	93.1	98.3	96.7	95.7	97.5
𝔻									
Estim. data	S1	87.8	81.6	86.4	87.1	89	78.6	91.1	90
	S2	27.1	51.8	48	53.1	74.7	86.2	92.6	88.7
	S3	51.6	67.2	73.5	73.9	40.1	74.5	73.9	64.6

Table 3. The F-measures recognition results using classifiers trained by training data sets from the same driver.

		F-measures (%)								
		Trained by S1			Trained by S2			Trained by S3		
		R1	R2	R12	R1	R2	R12	R1	R2	R12
𝔽										
Est. data	R1	96.7	91.4	97.6	90.2	87.1	90.3	90.3	88.5	90.1
	R2	86.5	98.3	95.7	96.8	97.3	97.4	94.9	97.3	97.1
𝔹										
Est. data	R1	68.5	36.6	73.2	76	77.8	74	70.1	65.9	70.1
	R2	6.68	91.7	89.5	88.7	91.5	91.9	88.9	90	91.1
ℂ										
Est. data	R1	96.5	95	96.1	92.1	85.9	91.5	94.8	95.5	95
	R2	94.8	96.1	92.1	93.8	96.9	96.1	90.1	93	94.9
𝔻										
Est. data	R1	87.8	74.5	86.1	51.8	19.2	47.8	73.5	60.9	76.3
	R2	85.7	89	85.5	67.2	86.2	81.8	90.3	88.5	90.1

4.3. *Discussions of modelling process by machine learning*

This section discusses the amount of data which is necessary for training the classification model (classifier). As the driving behaviour classification model is synthesised from the data-driven method, the accuracy of the driving state classification depends on the amount of the data used for training the model. As an example, Figure 12 compares the recognition accuracy of five driving states on road section R1 when using different amount of data. The first row of colour bars shows the case which the model is trained with only one trip data. The bottom row of colour bars shows the case which the model is trained with seven trips of driving data. As can be noticed from the figure, the driving state recognition result shows good accuracy from the fifth row, the classifier being trained by five trips of data.

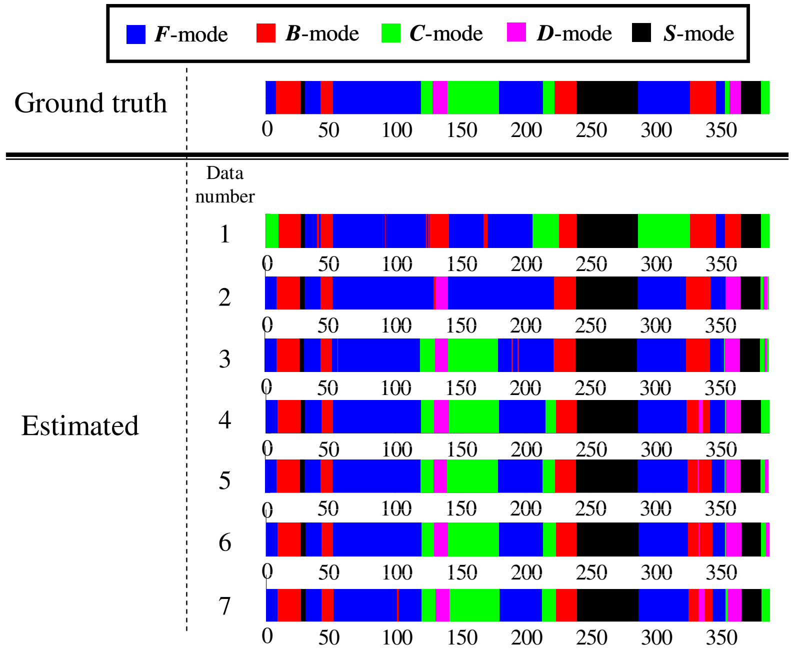

Figure 12. Driving state recognition results based on different amount of training data.

5. Driver model based on state estimation

This section describes a model when the driving state undergoes a transition from 'car following (F state)' to 'independent driving (C state)' based on the driving state estimation conducted in the previous section. As a representative scenario indicated in Figure 13, a leading vehicle ahead disappears due to some reasons, e.g. right turn, left turn or lane change. In such a driving state transition, the synthesised model can be used in advanced driver assistance systems for detecting unusual driving behaviour such as hurry driving or invigilant driving.

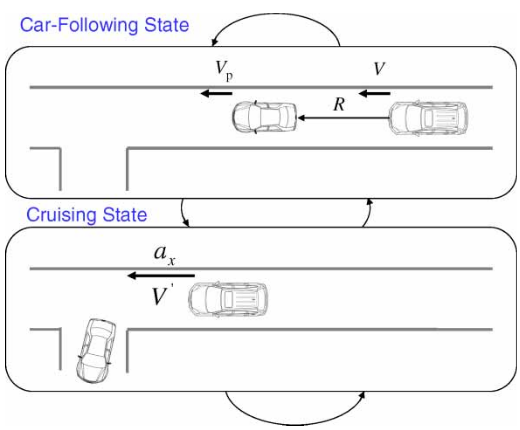

Figure 13. Driving state transition scenario: car-following to cruising.

Driver models describing the car-following and the independent cruising situations are addressed. From the information of the headway distance, the vehicle speed and the speed limit on each road section, the predicted values of the acceleration and the accelerator as well as the braking pedal strokes can be calculated. If the driver is driving based on an assumption that he always keeps the time headway constant at a desired value, the driver model for longitudinal control can be expressed in the form of the longitudinal acceleration as follows [14,15]:

$$a_{\mathrm{F}}^{*}(t) = K_{\mathrm{R}}\left[R(t) - T_{\mathrm{hw}}^{*} V(t)\right] + K_{\dot{R}}\dot{R}(t) \tag{16}$$

where, a_{F}^{*} indicates the desired longitudinal acceleration of driver in the car-following state, T_{hw}^{*} indicates the desired time headway of driver, K_{R} indicates the feedback gain of headway distance and $K_{\dot{R}}$ indicates the feedback gain of relative velocity. In the case of the cruising state, it can be assumed that the driver selects his own desired speed, and controls the pedal strokes to trace the selected speed. Consequently, in the cruising state, the driver model can be expressed in terms of the longitudinal acceleration as follows:

$$a_{\mathrm{C}}^{*}(t) = K_{\mathrm{V}}[V^{*} - V(t)] \tag{17}$$

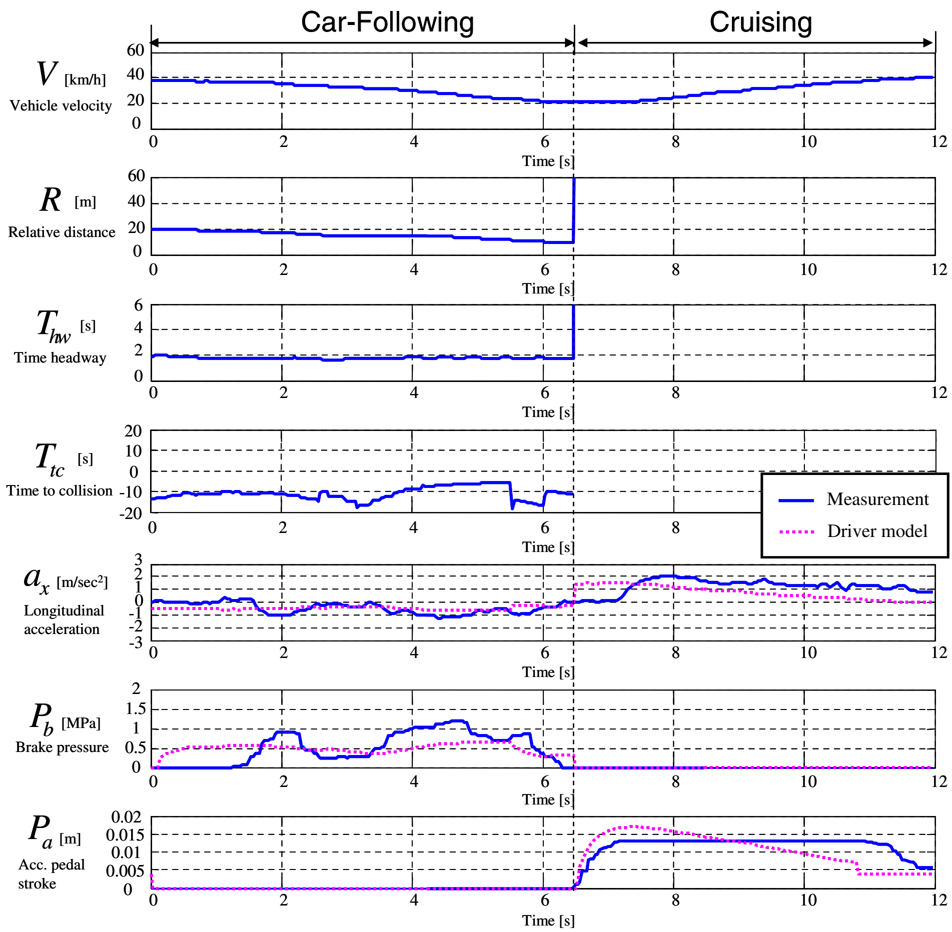

Figure 14. Driver behaviour modelling in driving state transition.

where a_C^* indicates the desired longitudinal acceleration of driver in the cruising state, V^* indicates the desired speed in cruising mode of driver and K_V indicates the feedback gain of vehicle speed. To get the target value of the longitudinal acceleration in each driving state, the driver pedal operation can be computed from the inverse dynamics of pedal operation to longitudinal acceleration as follows:
(*Brake pedal operation*)

$$P_b(s) = \frac{h_b}{\tau_h s + 1} a_i^*(s) \quad i = F, C \tag{18}$$

where, P_b indicates the brake pressure from foot brake operation, h_b indicates the gain of brake pressure with respect to acceleration, and τ_h indicates the time constant of first-order lag in driver pedal operation.
(*Accelerator pedal operation*)

$$P_a(s) = \frac{1}{\tau_h s + 1} \left[h_a a_i^*(s) + h_v V(s) \right] \quad i = F, C \tag{19}$$

where P_a indicates the accelerator pedal displacement, h_a indicates the gain of accelerator pedal stroke with respect to acceleration and h_v indicates the gain of accelerator pedal stroke with respect to velocity. Here, the term regarding the vehicle speed is also considered in order to compensate the influence of the running resistance.

Figure 14 shows an example of driving data during a driving state transition from the car following state to the cruising state. The measured and the estimated pedal operations based on the driving state recognition and the feedback model are compared. The result shows good consistency between the experimental data and the model-based data.

6. Conclusions

This paper describes an integrated modelling of driver behaviour, especially in longitudinal driver–vehicle dynamics, for the design of advanced driver assistance systems embedded with individual adaptation technology. Driving behavioural states focused in this paper comprise Car-Following (F), Braking (B), Cruising (C), Decelerating (D) and Stopping (S). The modelling procedure includes a driving state recognition (annotation) and a description of input–output relationship based on feedback control theory. Considering state transition of driving behaviour, BSLM based on logistic regressive model has been employed to deal with the sensor data annotation problem. The validations have revealed that this classifier can effectively recognise F, C and S while yielding relatively lower accuracies in recognising B and D. We also show that the cross recognitions between the different subject drivers or local roads are successful for F and C, which could lead to practical real-world applications when recognising the driver states of numerous drivers. Based on the driving state recognition result, the input–output descriptive driver models in car-following and cruising states are proposed. The validation result of the proposed driver modelling shows good consistency with the experimental data.

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Nomenclature

R	headway distance (m)
$\dot{R}$	relative velocity, i.e. derivative of R (m/s)
V	host vehicle velocity (m/s)
V_{p}	preceding vehicle velocity (m/s)
a_x	longitudinal acceleration (m/s^2)
X	GPS longitudinal coordinate (°)
Y	GPS latitudinal coordinate (°)
T_{hw}	time headway (s)
$T_{t\mathrm{c}}$	time to collision (s)
F	following state label
B	braking state label
C	cruising state label
D	decelerating state label
S	stopping state label
x_t	sensor data at t
$x_{1:t}$	sensor data sequence from initial to t
y_t	driving state label at t
F_{yt}	discriminative function of $x_{1:t}$ at t
G_{yt}	discriminative function of y_{t-1} at t
f_{yt}	weak learner of F_{yt} (decision stump) at t
g_{yt}	weak learner of G_{yt} (decision stump) at t
$p(y_t \vert x_{1:t})$	conditional probability of y_t given $x_{1:t}$
$\tilde{p}(y_{t-1})$	$p(y_{t-1} \vert x_{1:t})$
θ	decision stump threshold
α_{yt}	decision stump value at t when $x_t(i)$ is higher than θ
α'_{yt}	decision stump value at t when $x_t(i)$ is lower than θ
a^*_{F}	desired longitudinal acceleration of the driver in F state (m/s^2)
a^*_{C}	desired longitudinal acceleration of the driver in C state (m/s^2)
T^*_{hw}	desired time headway of the driver (s)
V^*	desired speed of driver in C state (m/s)
K_{R}	acceleration gain due to headway distance (1/s^2)
K_{V}	acceleration gain due to relative velocity in F state, and to vehicle speed in C state (1/s)
P_{b}	brake pressure from foot brake operation (MPa)
h_{b}	brake–pedal–stroke gain due to acceleration
τ_{h}	time constant of first order lag in driver pedal operation (s)
P_{a}	accelerator pedal displacement (m)
h_{a}	accelerator–pedal–stroke gain due to acceleration
h_{v}	accelerator–pedal–stroke gain due to velocity

References

[1] H. Yoshida, M. Nagai, T. Kamada, and Y. Shimozato, *Experiment and design of advanced brake assist system of active interface vehicle based on driver's gas pedal operation*, Rev. Autom. Eng. 26(2) (2005), pp. 237–243.
[2] P. Raksincharoensak, Y. Michitsuji, K. Maeda, and M. Nagai, *Continuous driving data sensing towards individual adaptation of advanced driver assistance system*, Proceedings of the 14th World Congress on ITS, Beijing, 2007.
[3] M. Ploechl and J. Edelmann, *Driver models in automobile dynamics application*, Veh. Syst. Dyn. 45(7–8) (2007), pp. 699–741.
[4] A. Liu and A. Pentland, *Towards real-time recognition of driver intentions*, Proceedings of 1997 IEEE Intelligent Transportation Systems Conference, 1997.

[5] A. Liu and D. Salvucci, *Modelling and prediction of human driver behaviour*, Proceedings of 9th International Conference on Human-Computer Interaction, 2001.
[6] N. Kuge, T. Yamamura, O. Shimoyama, and A. Liu, *A driver behaviour recognition method based on a driver model framework*, Proceedings of the 2000 SAE World Congress, 2000.
[7] Y. Amano, T. Sugawara, S. Nagiri, and S. Doi, *Driver support system by the prediction of driving manoeuvre*, Trans. Jpn. Soc. Mech. Eng. 70(698) (2004), pp. 2932–2939.
[8] T. Kumagai and M. Akamatsu, *Human driving behaviour prediction using dynamic bayesian networks*, Proceedings of JSAE Annual Congress, 2005, pp. 13–18.
[9] J. McCall and M. Trivedi, *Human behaviour based predictive brake assistance*, Proceedings of IEEE Intelligent Vehicle Symposium, 2006, pp. 13–18.
[10] A. Gerdes, *Driver manoeuvre recognition*, Proceedings of 13th World Congress on ITS, 2006.
[11] J. Lafferty, A. McCallum, and F. Pereira, *Conditional random fields: Probabilistic models for segmenting and labelling sequence data*, Proceedings of 18th International Conference on Machine Learning, 2001, pp. 282–289.
[12] R. Duda, P. Hart, and D. Stork, *Pattern Classification*, 2nd ed., John Wiley and Sons, New York, 2001.
[13] M. Shimosaka, T. Mori, and T. Sato, *Robust indoor activity recognition via boosting*, Proceedings of the 19th International Conference on Pattern Recognition (ICPR 2008), Tampa Florida, December, 2008.
[14] P. Fancher, Z. Bareket, and R. Ervin, *Human-centered design of an ACC-with-braking and forward-crash-warning system*, Veh. Syst. Dyn. 36(2–3) (2001), pp. 203–224.
[15] P. Zheng and M. McDonald, *Manual vs. adaptive cruise control – can driver's expectation be matched?* Transp. Res. C 13 (2005), pp. 421–431.