Driver Status Identification From Driving Behavior Signals

by

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This is to certify that I have examined this copy of a master's thesis by

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and have found that it is complete and satisfactory in all respects,

and that any and all revisions required by the final

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ABSTRACT

Driving behavior signals differ in how and under which conditions the driver use vehicle control units, such as pedals, driving wheel, etc. In this study we investigate how the driving behavior signals differ among drivers and among different driving tasks. Statistically significant clues of these investigations are used to define driver and driving status models. Experimental results over the UYANIK database are presented. Driver identification over 23 drives achieves 57.39% identification rate with the fusion of gas and brake pedal pressure classifiers. Driver identification system with reduced number of drivers suits better to real-life scenario. 85.21% of identification rate is achieved among 3 drivers. Driver status identification over 10 drivers with task and no-task classes yields a promising 79.13% identification rate.

Driving behavior is strongly related to past movements of drivers. In this thesis we aim to predict driving behavior for warning drivers about future incidents and decreasing car accidents caused by human factors. The proposed method is concerned with past samples of behavior signals and we use Hidden Markov Models to model driving behavior. Earlier findings have shown us that we can predict driving behavior with encouraging results in both driver dependent and independent experiments. The experimental results also show that distractive conditions have a certain effect on driving behavior as the prediction errors are significantly increasing in these conditions. Road conditions are also influential on driving.

ÖZ

Sürücü davranış sinyalleri; sürücünün pedal, direksiyon kontrol birimlerini nasıl ve hangi koşullar altında kullandığına gore çeşitlilik gösterir. Bu çalışmada farklı sürücüler ve farklı sürüş koşullarına gore davranış sinyallerinin nasıl değiştiği araştırılmıştır. Bu araştırmalardan elde edilen istatistiksel bilgiler kullanılarak sürücü ve sürücü statü modelleri tanımlanmış, UYANIK veritabanı kullanılarak elde edilen deneysel sonuçlar sunulmuştur. Gaz ve fren pedal basınç sınıflandırıcılarının füzyonu kullanılarak 23 sürücü üzerinden yapılan deneylerde %57.39 sürücü tanıma başarı oranı elde edilmiştir. Az sayıda sürücünün kullanıldığı sürücü tanıma sistemi, gerçek hayat senaryolarına daha fazla uyar. Bu amaçla 3 sürücü kullanılarak yapılan deneylerde %85.21 sürücü tanıma başarı oranı elde edilmiştir. Sürücülerin daha önceden belirlenmiş görevleri yaptıkları ve hiçbir görev yapmadıkları durumlar için 2 sınıf oluşturulup, 10 sürücü üzerinden sürücü durumu tanıma deneyleri yapılmıştır. Bu deneylerde %79.13 tanıma başarı oranı sağlanmıştır.

Sürücü davranışları, sürücünün önceki davranışlarıyla büyük ölçüde ilintilidir. Bu çalışmada, sürücüleri olası tehlikeli olaylara karşı uyarmak ve insan kaynaklı trafik kazalarını minimuma indirmek için sürücü davranışlarını kestirecek yöntemler araştırılmıştır. Önerilen yöntem, sürücü davranış sinyallerinin geçmişteki örneklerini kullanmak ve Gizli Markov Modelleri'ni kullanarak sürücü davranışlarını modellemek üzerinedir. Elde edilen sonuçlar hem sürücüden bağımsız hem de sürücüye bağımlı deneyler için makul değerlerdir. Ayrıca, deneylerden edindiğimiz sonuçlara gore sürücüyü rahatsız edici koşulların sürücü davranışı üzerinde kesin bir etkisi olduğu görülmüştür. Bu rahatsız edici koşullar altında sürücü sinyallerini kestirme hataları ciddi ölçüde artmıştır. Yol koşullarının da sürücü davranışı kestirme de etkili olduğu gözlemlenmiştir.

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CHAPTER 1

INTRODUCTION

Recent developments in man-machine interaction have created a wide range of applications. Among those applications human-vehicle interfaces have been studied extensively in the recent literature. Next-generation human-vehicle interfaces will likely incorporate biometric person recognition, using speech, video, images, and analog driver behavior signals to provide more efficient and safer vehicle operation. Furthermore, driving behavior signals, such as pedal signals, velocity, car-following distance, yield important clues on driving behavior status and driver's cognitive stress/distraction.

There have been significant efforts on investigation of driving behavior patterns using driving behavior signals. Kurahashi et al. used driving behavior signals to quantify workload factors for driving behavior modeling [1]. Center for Acoustic Information Research at Nagoya University has been collecting multi-modal driving behavior signals since 1999 [2]. Their early studies investigate cepstral analysis of driving behavior signals [3] and modeling driver behavior as car-following and pedal operation patterns [3, 4]. Recently, they investigate near-miss accidents by means of interviews to determine driver behavior and cognitive state immediately before the incident [5]. Driver identification from biometric and driving behavior signals has been investigated within a multi-modal decision fusion system in [6].

Car following data collection and modeling have also been investigated across different research centers [7, 4]. Predicting driver's future actions with the resultant behavior and past observations have been studied with implications to model the impact of Intelligent Transport Systems (ITS) [5, 8]. Tezuka et al. investigate prediction of driving behavior signals by capturing time-series steering angle data at the time of lane change with conditional Gaussian models and Bayesian networks [8].

A multi-modal signal processing system for robust stress detection in urban driving scenarios has been proposed in [9]. Marinova, Devereaux and Hansman has studied the effects of cell phone conversations on driver reaction time and situation awareness at different levels of cognitive with hands-free and hands-held cell phone configurations [10]. Cognitive workload and driver experience, using a secondary task method, the peripheral detection task (PDT) in a field study has also been explored [11].

Nagoya University CIAIR center leads the effort on international research coordination of driving behavior signal processing based on large scale real world database [2]. Within this research coordination, UTDrive of University of Texas at Dallas collects multi-modal driving behavior data [12]. UTDrive investigates driver's cognitive stress/distraction to adapt interactive systems for improved safety. Similarly, the Drive- Safe consortium, which has partners from academia and industry in Turkey, collects a similar multi-modal driving behavior corpus to create conditions for prudent driving [13].

In this thesis as a partner of the Drive-Safe consortium, we investigate driver identification, driving status identification and driver behavior prediction under different cognitive stress/distraction conditions using driving behavior signals. Our objective is to search out and examine the effects of cognitive distraction conditions on driving behavior and inquire whether the driving behavior signals are characteristic information for every driver. We compare our findings with different studies' results on similar databases in Japan and USA. We also investigate task identification performances. Earlier findings are presented in [17].

Significant contributions of this thesis are defined within the following three problems:

1.1 Driver Identification

Identification of a driver using behavioral signals is one the most interesting signal processing problems. A driver identification method, proved to achieve high performance can be used in many applications, such as driver verification for security purposes and customization of vehicle according to driver's behavior characteristics. In the study of methods for recognizing drivers, driving behavior signals play a central role. In this study we only use driving behavior signals such as the vehicle speed, gas pedal pressure, brake pedal pressure and the distance from the vehicle in front. First, we investigate the characteristics of these signals and present a selected set of driving statistics. We propose an identification method and employ this method on behavior signals respectively. Also, we analyze the performance of fusion methods on the identification problem. Identification results are presented in the Experiments section.

1.2 Driver Status Identification

Distractive conditions cause important safety problems to drivers. Studies have shown that nearly 80% of traffic accidents occur because of the driver inattention, which are commonly result of distractive conditions. Navigation systems and other services in vehicles introduce many secondary driving tasks that can increase accident risk. Thus, developing a distraction detection method would be very beneficial for in-vehicle system to reduce the effects of distraction. In this study, driving experiments were done under some distractive conditions, which can be considered as the secondary driving tasks stated above. These tasks are dialog on cell phone, including route navigation and online banking, conversation with passenger on board, signboard and license plate reading. First, we plot the histograms of each driving behavior signals under driving tasks respectively. Effects of distractive conditions on drivers are analyzed by comparing these histograms. Next, we try to detect distractive conditions by employing the same method used for driver identification. Identification results are presented in the Experiments section.

1.3 Predicting Driver Behavior

Human factors play a big role in traffic accidents. Predicting driving behavior is an important issue because it has a significant effect on decreasing human-caused accidents. Drivers' behavior is strongly related to their past actions, so in this research we construct a model concerning with drivers' past movements by using Hidden Markov Models. Selecting the adequate number of HMM states and past samples is crucial for enhancing the system performance. Also we investigate the influence of road conditions and distractive conditions on our prediction model.

CHAPTER 2

DRIVING BEHAVIOR SIGNAL CHARACTERISTICS

Driving signals differ in how and under which conditions the driver use vehicle control units, such as pedals, driving wheel, etc. We aim to model individual differences among the selected drivers and identify the drivers by using gas pedal pressure, brake pedal pressure, vehicle velocity and fusion of these signals. We also benefit from the car following distances. Driver behavior modeling has also been studied with encouraging results in the U.S., Japan, Italy and Singapore by using similar driving behavior signals collected with different vehicles. Japanese research demonstrates that the driver model based on pedal operation signals achieved a driver identification rate of 76.8 % for 276 drivers [4]. It is not difficult to guess characteristics in driving behavior differ from person-to-person under some distractive conditions. In order to search out and examine the effects of these distractive conditions we investigate how the driving behavior signals differ among some driving tasks. Statistically significant clues of this investigation are used to define a driving status model. Besides these, we investigate driver behavior prediction with driver's past movements by using the same database. Behavior signals are clustered into different segments and we employ the prediction method on all these segments. This section presents general characteristics and statistics of the driving behavior signals from the UYANIK database, feature representation of these driving behavior signals, and the statistical clustering, identification framework for the driver and driving status and predicting driver behavior.

2.1 Data Collection

Driving behavior data was supplied by Drive-Safe Consortium in Turkey with the test vehicle, UYANIK, which is a sedan car equipped with various sensors. The UYANIK database includes synchronous audio-visual recordings, CAN-Bus readings, pedal sensor recordings, 180^0 laser range finder and XYZ accelerometer recordings as seen in Fig. 2.1 [13]. “Nagoya Vehicle” in Japan and “UT-Drive” in Dallas, Texas, USA have also been equipped in a similar way.

The data collection route, shown in Fig. 2.2 is around 25 km at about 40 minutes, starting and ending at the OTAM Research Center in the ITU Campus in Ayazaga. It consists of two 1.5 km very busy city sections, followed by the TEM Highway with much less traffic. Next comes the city streets in Etiler, Akatlar, Levent, 4. Levent, Ayazaga and the drivers go back to OTAM at ITU campus. The last segment is very busy with local traffic. Among the database we benefit from 23 drivers’ behavior signals, 20 of them are male and remaining are female. Each driver drove the car on the same route; however road conditions may differ depending on traffic jam and weather in İstanbul. There are four primary tasks in the UYANIK database: i) *reference driving* which includes no specific driving task, ii) *dialog on cellphone* which includes on-line banking application and navigational dialog, iii) *signboard reading* in which driver reads road-by signs and license plates aloud, and iv) *dialog with passenger* where driver talks with the on board passenger.

Fig. 2.1 Sensors in the data collection vehicle upperleft clockwise: cameras, navigator area and lab bench for data acquisition systems, laser scanner, IMU XYZ accelerator, break pedal pressure sensor, headset/mics, and EEG cap [13]

2.2 Driving Behavior Signals

We consider gas and brake pedal pressure signals, velocity from Can-Bus and car following distance from the laser range finder as driving behavior signals. The gas, brake and velocity signals are all sampled at 32 Hz, and the laser range finder sweeps 180^0 at every 2 seconds. Samples of driving behavior signals are given in Fig. 2.3, where the brake and gas pedal pressure levels, velocity and car following distance are given from top to bottom.

Fig 2.2 Data collection route in İstanbul [13]

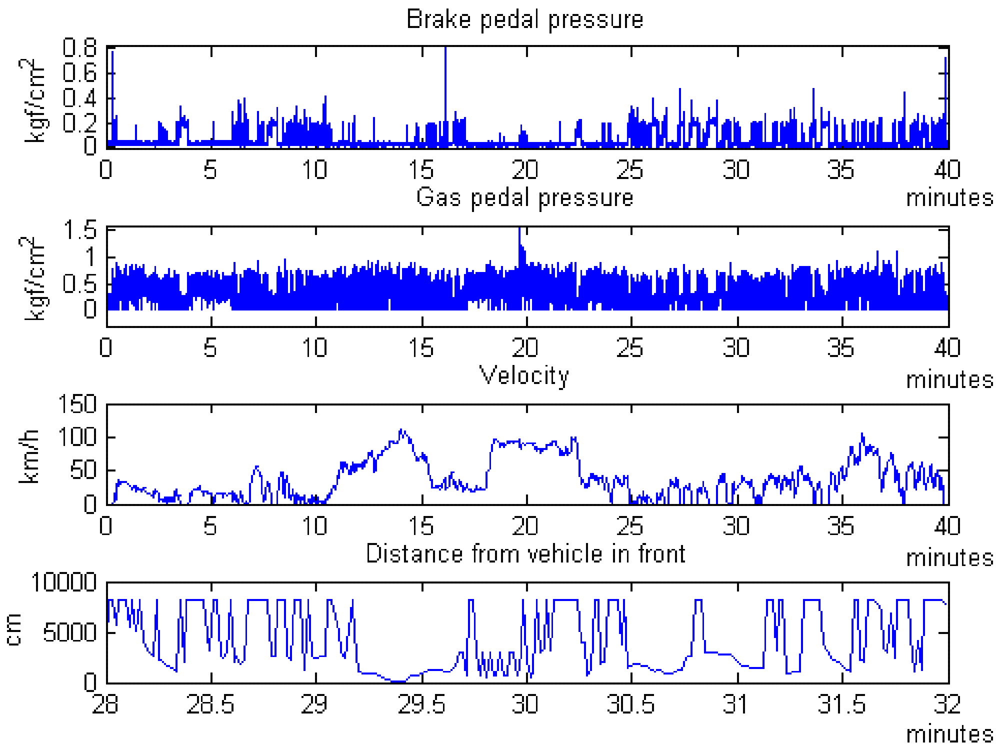


Fig. 2.3 Driving behavior signals of a driver from the UYANIK database

The laser range finder in front of the vehicle records two-dimensional (x,y) data consisting of horizontal and vertical distances. Fig. 2.4 shows the Laser Scan Reading and the photo for a selected driver recorded at 12:56 PM on April 6, 2007. Truck on the right is between -200 to +800 cm, the white truck is away 22 meters, and the vehicle on the next lane (left) is about 23 meters ahead [13].

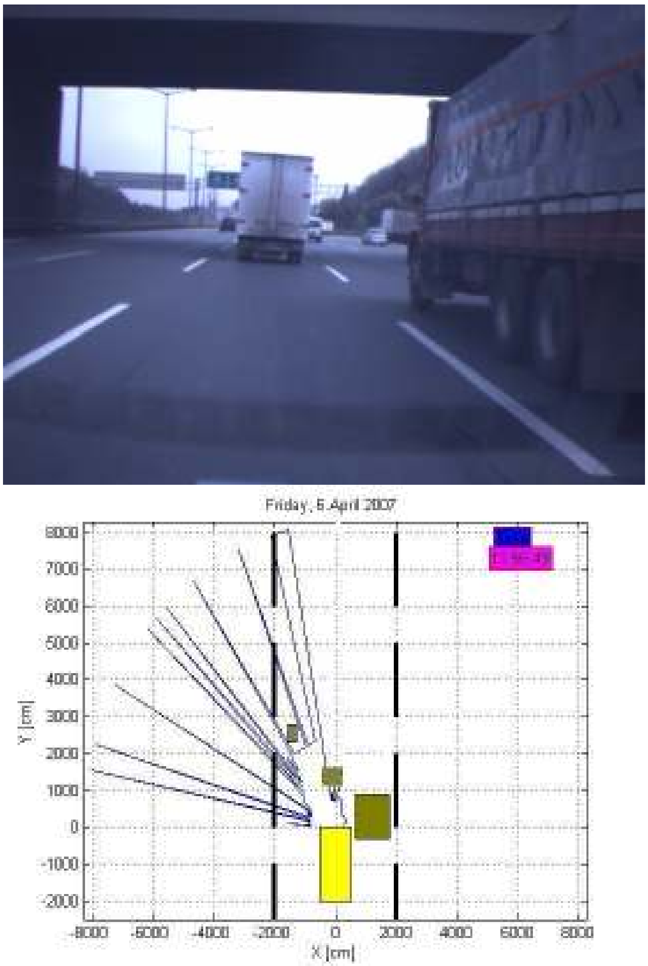


Fig. 2.4 Laser Scan Reading and the photo for a selected driver

Histograms of the driving behavior signals over all 23 drivers from highway and city traffic conditions are shown in Fig. 2.5. Histograms show that, on highway drivers rarely use brake pedal and much more use gas pedal. As a result of this, people reach higher velocity levels on highway. The maximum range that the laser can sweep is about 80 meters and generally most of the drivers exceed this distance on highway.

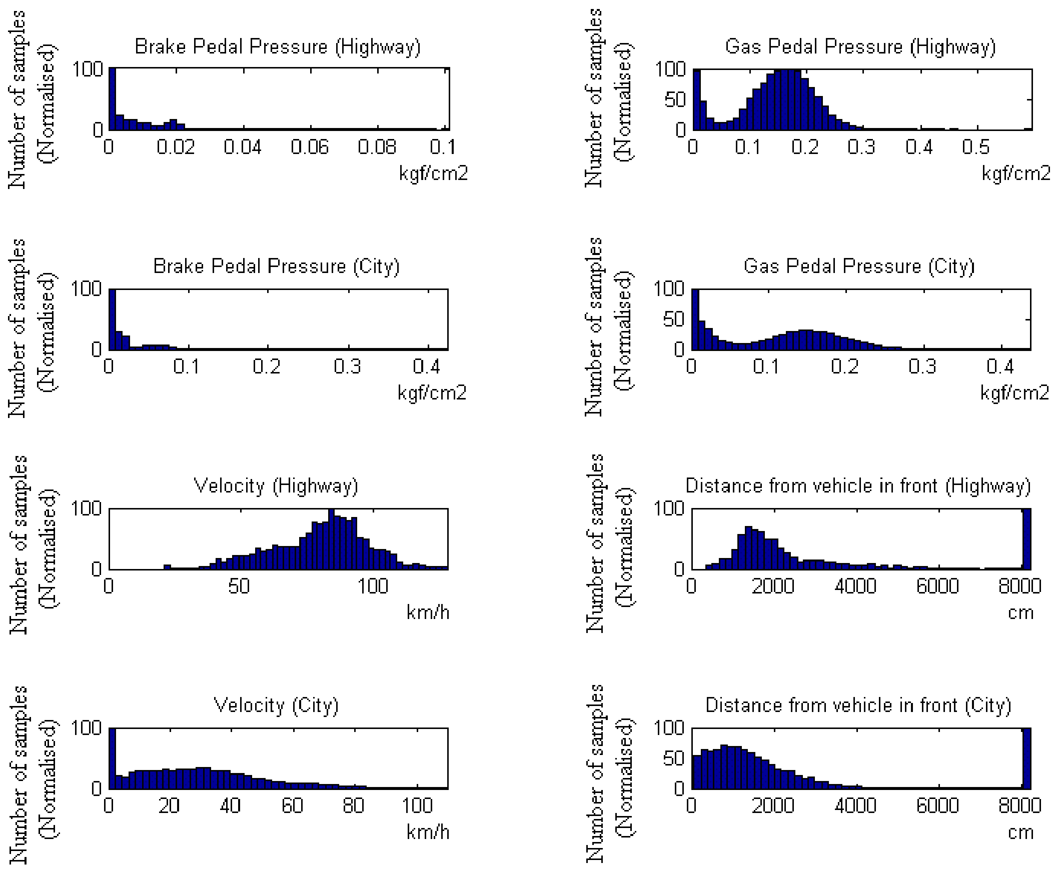


Fig. 2.5 Histograms of the driving behavior signals from highway (top) and city (bottom) traffic

Histograms of the driving behavior signals, taken from two randomly selected drivers are shown in Fig 2.6. The driver on the left side of the figure prefers driving faster and rarely uses the brake pedal. Also he/she generally keeps distance with the vehicle in front for all road conditions while the other driver prefers following a vehicle with closer distances where he/she faces traffic jam and much more uses brake pedal. Such differences are clear indications that driving behavior signals differ across drivers.

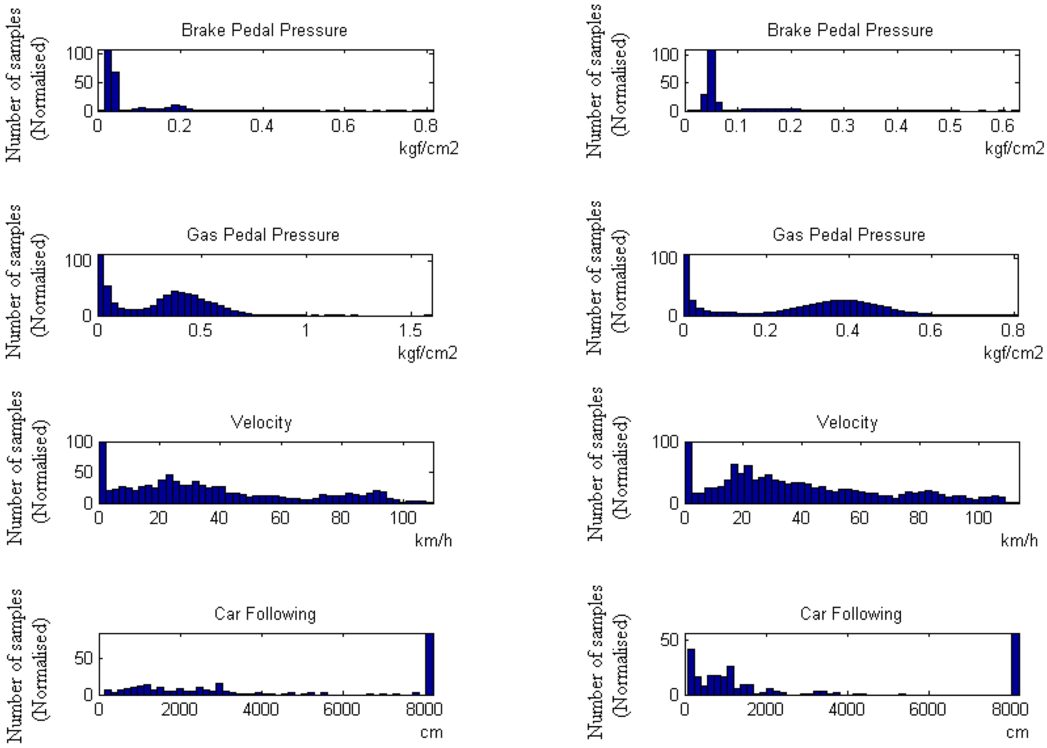


Fig. 2.6 Histograms of driving signals for two drivers:driver one on the left, driver two on the right columns.

CHAPTER 3

DRIVING BEHAVIOR MODELING

Modeling driver behavior is very important in enhancing the safety of the drivers and pedestrians. Driver authentication, early warning systems for vehicles and other technologies for security purposes can be given as the application areas of driver behavior modeling. Driving behavior is a cyclic process. Basic dynamics of this process is shown in Fig. 3.1. The driver determines the action to take by considering the road environment and operates the gas or brake pedal. Velocity of the vehicle changes according to the driver's operation and the distance from the vehicle in front (road environment) also changes according to the vehicle status.

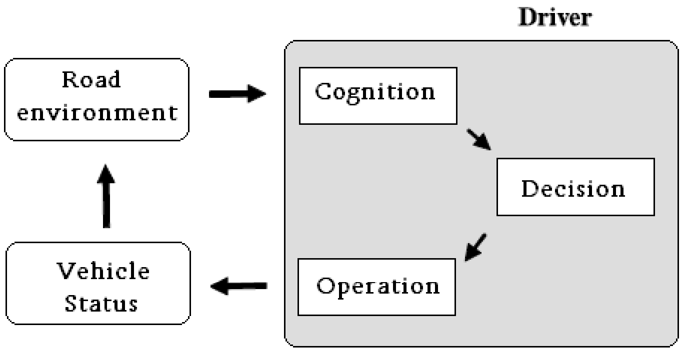


Fig. 3.1 Cyclic process of driving behavior [16]

In this chapter we discuss feature extraction, driver identification, driver behavior signal prediction and their role for driver behavior modeling. Driver identification is based on recognition of driving feature vectors using a statistical model. Our model is designed using a training and test procedure. In the training part, our algorithm learns the model of the data from a training set constructed by extracting the driver behavior features. In the testing part accuracy of the algorithm is measured on the testing set, which is completely different from the training set. Here, feature extraction is a key point for our algorithm to select reliable features that represent the true underlying distribution of driver behaviors.

3.1. Feature Extraction

First preprocessing step is the high pass filtering of the driving signals to remove the DC component. Gas pedal pressure, brake pedal pressure and vehicle velocity signals are all filtered with the following high-pass filter:

$$H(z) = \frac{1 - z^{-1}}{1 - 0.9999z^{-1}} \tag{3.1}$$

which has the frequency response as shown in Fig.3.2.

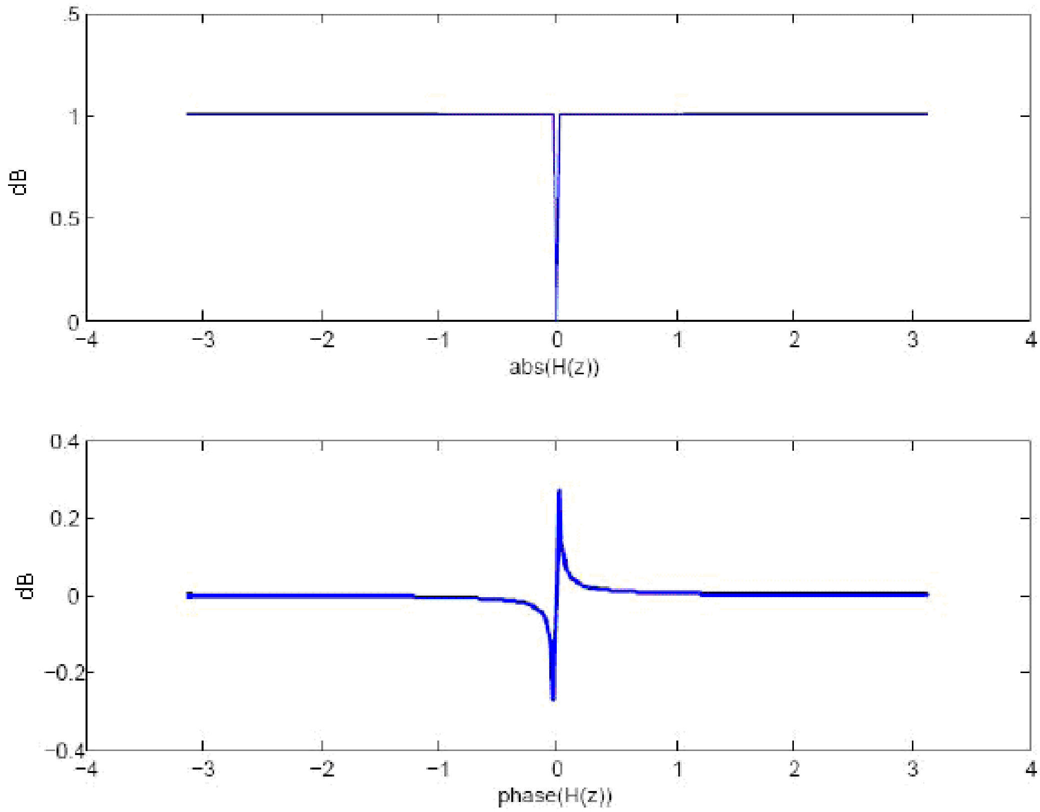


Fig. 3.2 Frequency response of the high-pass filter

The input data is too large to be processed, so we need to transform it into a reduced representation set of features. We need to capture significant information from driving behavior signals. Spectral analysis is one option. In driver modeling, hitting a gas or brake pedal is filtered with driver model represented as the spectral envelope. Spectral envelopes of pedal operation signals represent the differences in pedal operation patterns. These spectral envelopes are similar in the same driver and different among different drivers. Using this property we apply the cepstrum method, known as a source/filter separation method, to perform feature extraction. Research dictates us to conclude that using raw signals results in worse performance rates when compared to the cepstral features [4]

In this study we extract cepstral features for the gas and brake pedal pressure and velocity signals, which are sampled at 32 Hz. The cepstral features are extracted over 800 ms windows for every 96 ms frames as shown in Fig. 3.3. The cepstral feature is defined as the first K coefficients of the discrete cosine transform of band-pass filtered log-magnitude spectra,

$$f_k = DCT\{BPF\{\log|F\{\bar{x}(n+kT)\}|\}\} \tag{3.2}$$

where k is the frame index, $\bar{x}(n+kT)$ is the windowed signal of duration T. Band-pass filter picks 1-13 Hz spectral components for brake signal and 1-6.5 Hz for gas and velocity signals. The dimension of the feature vector is set as k=10. Feature extraction process is summarized in Fig. 3.4.

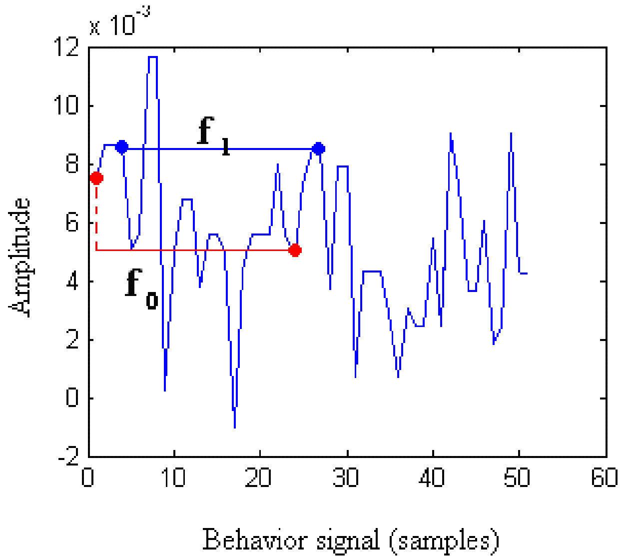


Fig 3.3 Feature extraction parameters

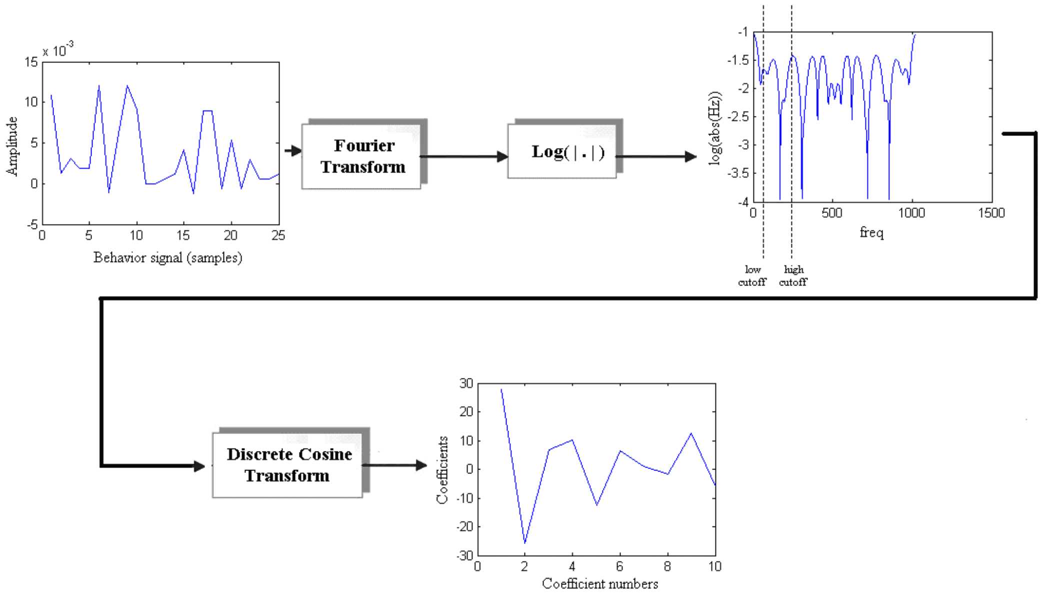


Fig 3.4 Feature extraction process

3.2. Driver Identification Model

The ability to identify a driver and his/her driving behaviors is related with how he/she hits the gas and brake pedals. We model these pedal operation patterns with Gaussian mixture models (GMM) in a maximum likelihood criterion so that the conditional probability is maximized for given conditions.

The maximum a posteriori probability solution to the N-class identification problem requires computing $P(\lambda_n \mid f)$ for each class λ_n, n = 1,…,*N*, given a feature vector f representing the sample data of an unknown class. An alternative is to employ the maximum likelihood solution, which maximizes the class-conditional probability,

$$\lambda^* = \arg\max_{\lambda_n} \log P(f \mid \lambda_n) \tag{3.3}$$

Furthermore, the likelihood scores coming from different feature types can be combined at decision level using weighted summation rule,

$$\lambda^* = \arg\max_{\lambda_n} \sum_k \alpha_k P(f_k \mid \lambda_n) \tag{3.4}$$

where $0 \le \alpha_k \le 1$ is the weight of the k-th feature type and $\sum_k \alpha_k = 1$.

Computation of class-conditional probabilities needs a prior modeling step, through which we estimate a probability density function of feature vectors for each class n = 1,…,*N* from an available training data. The class conditional probability density functions are modeled using the Gaussian mixture densities,

$$P(f \mid \lambda_n) = \sum_{k=1}^{M} \omega_k N(f; m_k, \Sigma_k) \tag{3.5}$$

where m_k and Σ_k are respectively mean vector and covariance matrix of the k-th mixture, and M is the total number of mixtures.

3.3 Driver Behavior Signal Prediction

Every year, traffic accidents lead to several fatalities and injuries. Human error is blamed as the primary cause for these accidents. Driver behavior modeling is extremely important to warn drivers about future incidents based on predicting driving actions. Similar studies have built driving behavior models to predict future action by using past movements. Kishimoto and Oguri applied to Dynamic Bayesian Networks to construct a behavior model for inference of stop behavior [14]. They have revealed that using past movements has a great influence for predicting stop probability. We propose a linear prediction method for driver's action based on driving behavior. We try to estimate the target samples from *N* recent samples of all behavior signals. The consistency of the predicted signal and the actual signal may give us an idea about driving quality.

In order to predict driver behavior signals, we construct a prediction model concerning with past movements of driver by using Hidden Markov Models. The hidden states are valid stages of a dynamic process and HMMs lead probabilistic transitions among different stages. We employ three driving data, brake, gas pedal strokes and velocity for our model. Flowchart of predicting driver behavior is shown in Fig. 3.5.

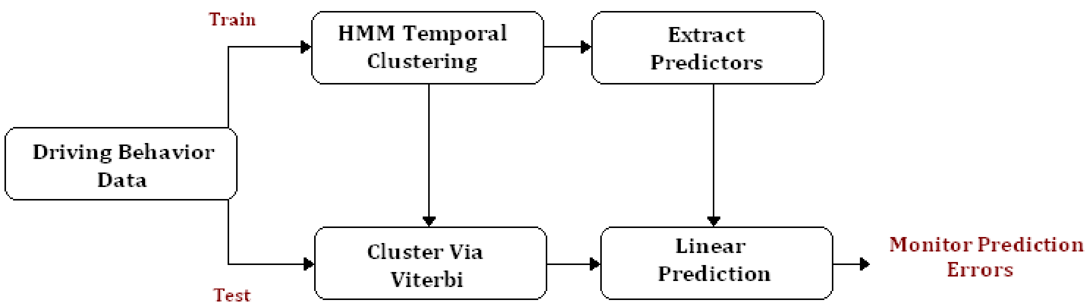


Fig. 3.5 Flowchart of predicting driver behavior

First we build a temporal correlation between all driving signals using HMM structure. Then we apply linear prediction to predict the desired driving behavior sample. The state sequence of the system is determined by using the Viterbi algorithm, which calculates the log-maximum likelihood of a series of observations given a particular HMM.

In each segment, constructed by HMM clustering we perform a linear prediction analysis to estimate current driving behavior sample from N recent driving behavior samples. We construct the feature vector $d(n) = [b(n), g(n), v(n)]$ where b, g and v vectors denote the direct samples taken from brake pedal pressure signal, gas pedal pressure signal and velocity signal of the corresponding segment respectively. Our prediction method is described as follows:

$$\hat{s}(n) = P([d(n-1), d(n-2), ..., d(n-i)]) \tag{3.6}$$

where $\hat{s}(n)$ is the sample to be estimated and i is the number of past samples used. We construct a feature vector f_n by combining the driver behavior samples.

$$f_n = [d(n-1), d(n-2), ..., d(n-i)] \tag{3.7}$$

The mean removed feature component can be extracted as,

$$x_n = f_n - \bar{f} \tag{3.8}$$

where $\bar{f}$ is the mean vector of f_n sequence.

In a similar way, the mean removed target sample can be extracted as,

$$y = y_n - \bar{y} \tag{3.9}$$

where y_n is the current sample and $\bar{y}$ is the mean of the driving behavior signal at current state. The linear estimator yields to the Yule-Walker equations,

$$R_{yx} = \begin{bmatrix} R_{yx0} \\ R_{yx1} \\ \vdots \\ R_{yxp-1} \end{bmatrix}$$

$$= \begin{bmatrix} R_{x0x0} & R_{x0x1} & \cdots & R_{x0xp-1} \\ R_{x1x0} & R_{x1x1} & \cdots & R_{x1xp-1} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ R_{xp-1x0} & R_{xp-1x1} & \cdots & R_{xp-1xp-1} \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_{p-1} \end{bmatrix}$$

$$= R_{xx} w \tag{3.10}$$

where R_{yx_i} and $R_{x_i x_j}$ are the correlation of *y, x_i* and *x_i, x_j* signals, respectively $R_{yx_i} = E\{yx_i\} = \frac{1}{M}\sum_{i=1}^{M} y_i x_i$ and $R_{x_i x_j} = E\{x_i x_j\} = \frac{1}{M}\sum_{i=1}^{M} x_i x_j^T$. The linear prediction yields a solution for the LP filter w as,

$$w = R_{xx}^{-1} R_{yx} \tag{3.11}$$

Target sample can be estimated as,

$$\tilde{y}_n = xw + \bar{y} \tag{3.12}$$

[15].

We can also measure the prediction errors by using the minimum mean squares error (MSE) which is calculated as

$$MSE = E\{\| y_n - \tilde{y}_n \|^2\} \tag{3.13}$$

CHAPTER 4

EXPERIMENTS

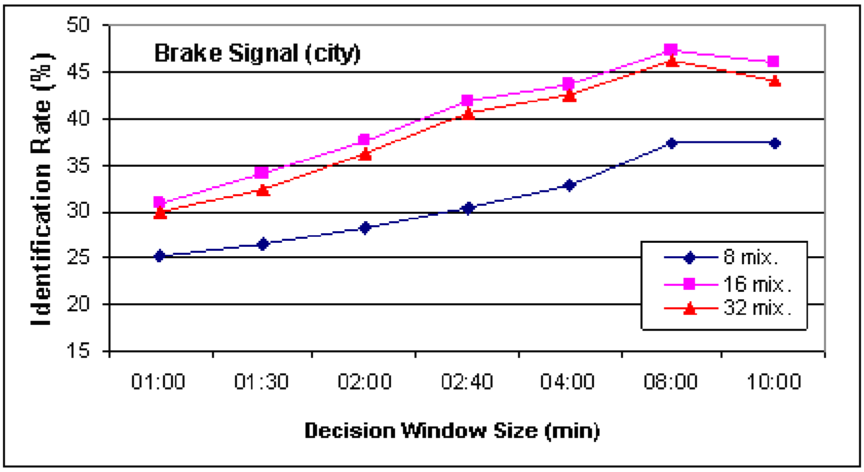
In the experimental evaluations we use two subsets from the UYANIK database. The first subset, U-DRIVER, includes 23 drivers to be used for the driver identification evaluation (3 of these drivers are not used for the car following task since they miss laser range information). The second subset, U-TASK, includes 10 drivers to be used for the driving task identification. Driver identification performance for a particular task-domain depends on the selection of accurate training database of interest in that domain. So, in order to achieve more realistic identification results we divide the U-DRIVER into 3 groups. Assuming that a vehicle is generally used by a limited number of different drivers, each of these groups is arranged in 20 subgroups including 3, 4 and 5 drivers respectively. Driver identification is performed for all these 60 subgroups independently. Also we benefit from this subset in order to predict driver behavior concerning with driver's past movements. The four primary tasks are transcribed on the U-TASK subset. In all driver and task identification evaluations, we use 5-fold cross-validation, where the available database is divided into five equal length segments (the first segment starts with the beginning of the driving session, the second one starts with the end of the first segments and the others follow the same procedure) and evaluations are performed over leave-one-segment-out train and test scheme. In driver behavior prediction evaluations we use 4-fold cross validation.

4.1. Driver identification

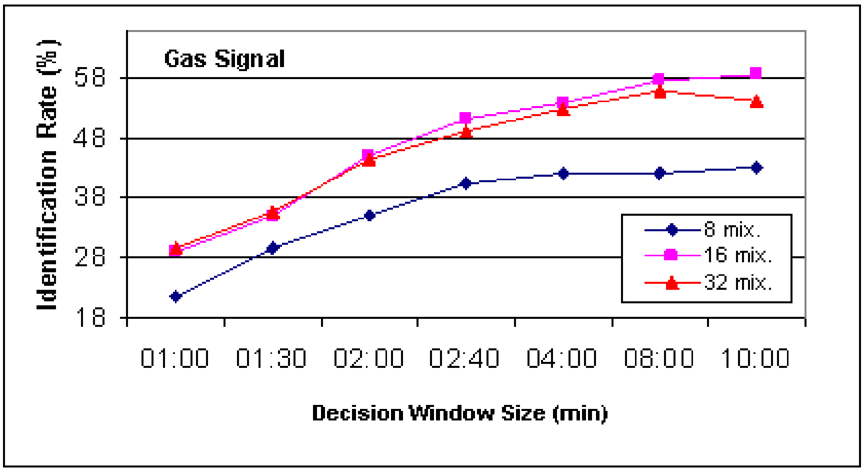
Every driver has characteristic driving behaviors. They vary in how they use the gas and brake pedals and how much distance they keep when following a vehicle. Considering the histograms in Fig. 2.5, it is not difficult to guess characteristics in driving behavior differ from driver to driver.

As described in Section II-III, the gas, brake and velocity signals are all sampled at 32 Hz. and the cepstral features are extracted over 800 ms (25 samples) of windows for every 96 ms (3 samples) of frames. Fig. 4.1 shows the driver identification performance over the U-DRIVER database including 23 drivers for brake pedal pressure, gas pedal pressure and velocity signals using cepstral coefficients and GMM classifier with varying number of mixtures. For identification purpose we use different decision window lengths and calculate the features for every 30 seconds of frames. Since brake pedal is not used frequently on highway, driver identification using brake pedal is performed only on city driving recordings.

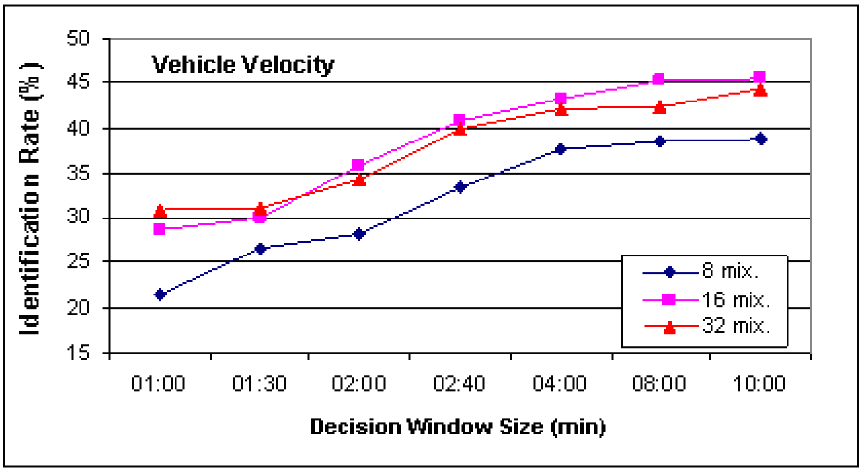
As shown below, the gas pedal pressure signal yields better performance than the brake pedal pressure signal. This is possibly due to the more frequent use of gas pedal by drivers. Best identification results for all behavior signals are obtained by using GMM classifiers with 16 mixtures over 8-10 minutes of decision windows. The unimodal driver identification rates are all below 60%, which presents a fair driver identification system with possible room to improvement.



(a)



(b)

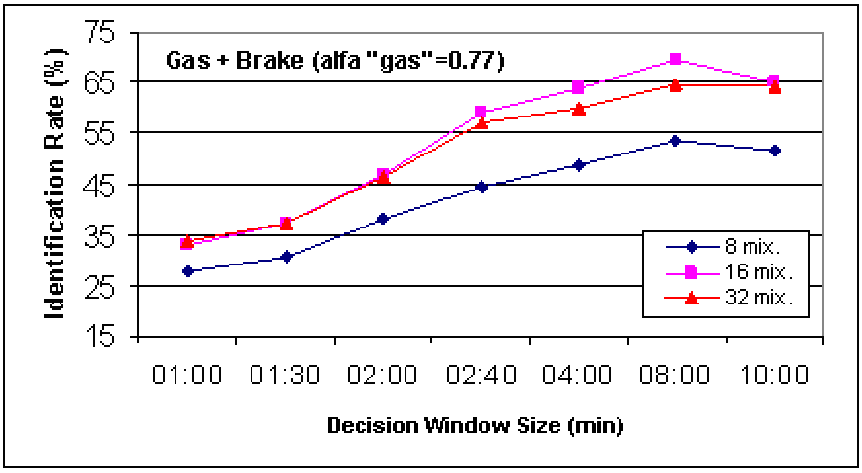


(c)

Fig. 4.1 Identification rates for the (a) gas pedal pressure, (b) brake pedal pressure and (c) velocity signals

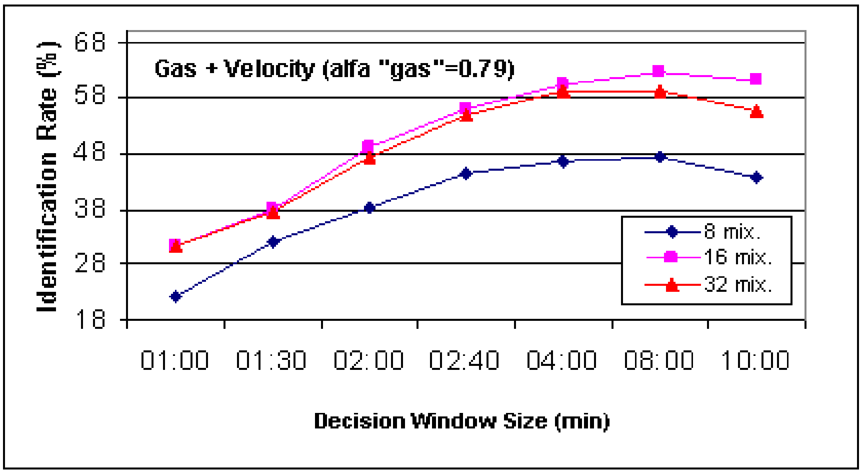
For a possible improvement, we perform decision fusion of classifiers of different driver behavior signals. We investigate the fusion of classifiers over gas, brake and velocity signals, and identify fusion structures with improved identification rates.

Fig. 4.2 presents decision fusion results of the driver identification system over different decision window sizes. The optimal weights of the classifiers in the decision fusion are set experimentally. The resulting weights are set as α_g = 0.77 in the brake (B) and gas (G) fusion, α_g = 0.79 in the velocity (V) and gas (G) fusion, and α_g = 0.70, α_b = 0.15, α_v = 0.15 in the gas, brake and velocity fusion. The best identification result is obtained as 69.5% with the fusion of gas (G) and brake (B) pedal pressure signals by using 16 mixtures of GMM. The best scenarios for all modalities are summarized in Fig. 4.3. We can easily observe from these results that decision fusion method significantly increases our system performance.



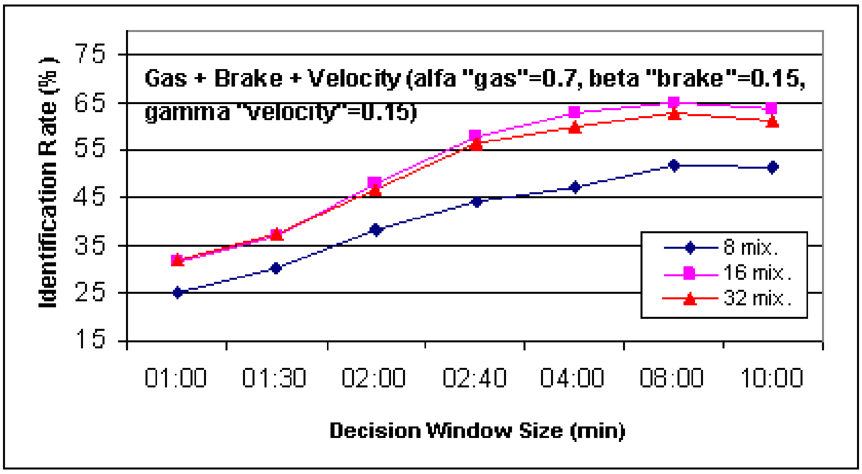
Gas + Brake (alfa "gas"=0.77)
Identification Rate (%)
75
65
55
45
35
25
15
01:00
01:30
02:00
02:40
04:00
08:00
10:00
Decision Window Size (min)
8 mix.
16 mix.
32 mix.

(a)



Gas + Velocity (alfa "gas"=0.79)
Identification Rate (%)
68
58
48
38
28
18
01:00
01:30
02:00
02:40
04:00
08:00
10:00
Decision Window Size (min)
8 mix.
16 mix.
32 mix.

(b)



(c)

Fig. 4.2 Identification rates for the decision fusion of (a) gas pedal pressure + brake pedal pressure, (b) gas pedal pressure + velocity and (c) gas pedal pressure + brake pedal pressure + velocity signals

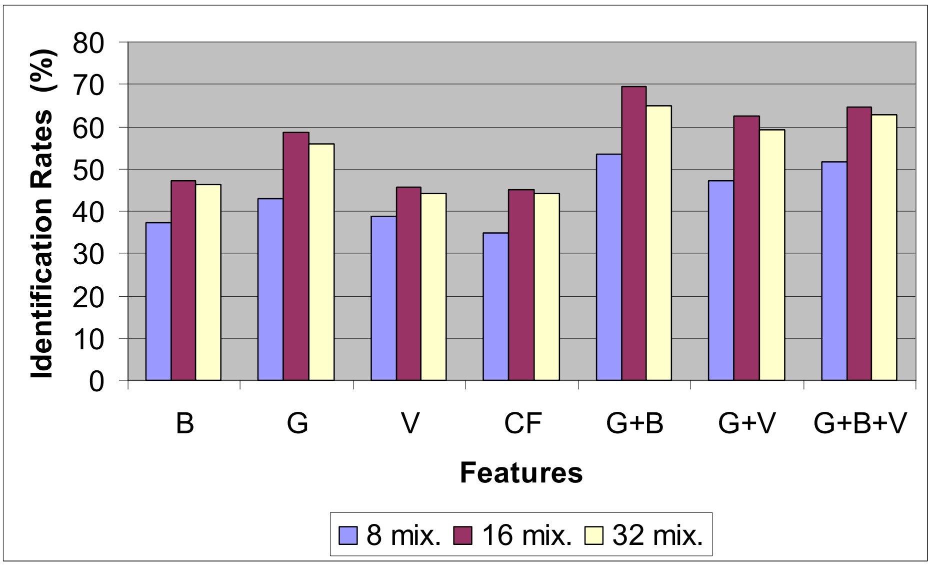


Fig. 4.3 Comparison of identification rates for unimodal and multimodal classifiers

Car following distance can also be used to identify a driver. Car following distance measures are collected with a laser range finder. The laser range finder sweeps 180^0 at every 2 seconds and measures the distance to the nearest object at each angle. We use the distance at 90^0 to obtain the distance with the vehicle in front. Since the maximum range that the laser can sweep is about 80 meters and most of the drivers exceed this distance on both highway and two-way roads, we only employ the car following distance signals on one-way roads. For one-way roads, the car following task is around 4 minutes long for each driver.

Fig. 4.4 shows the identification results for the car following distance signals over the U-DRIVER database including 20 drivers at different test lengths. Since the length of the task is rather short, selecting the decision window size is very crucial. The best performance is achieved as 45% with the 16 mixture GMM classifier with 150 seconds decision windows.

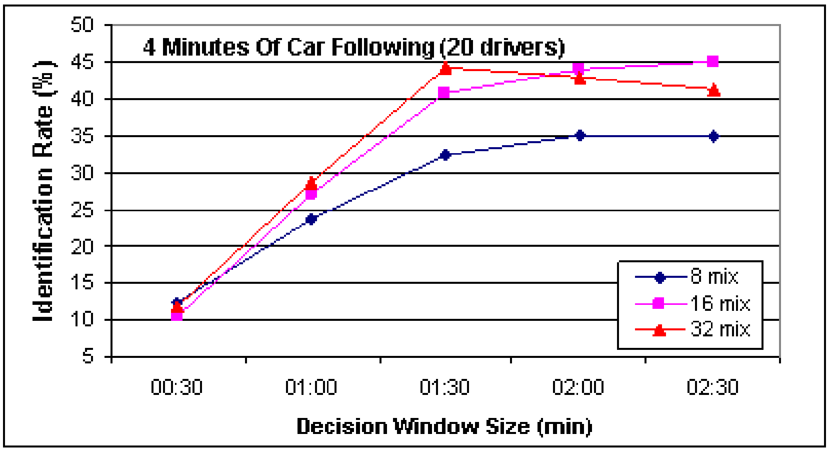


Fig. 4.4 Identification rates for the car following distance signals

As the accelerator pedal is operated directly by the driver, it yields us the best feature to identify the driver characteristics. Since the distance from the vehicle in front and vehicle velocity are the results of the driver's pedal operations, we achieve poor results by using only these features. Driver identification results are all summarized in Fig. 4.5.

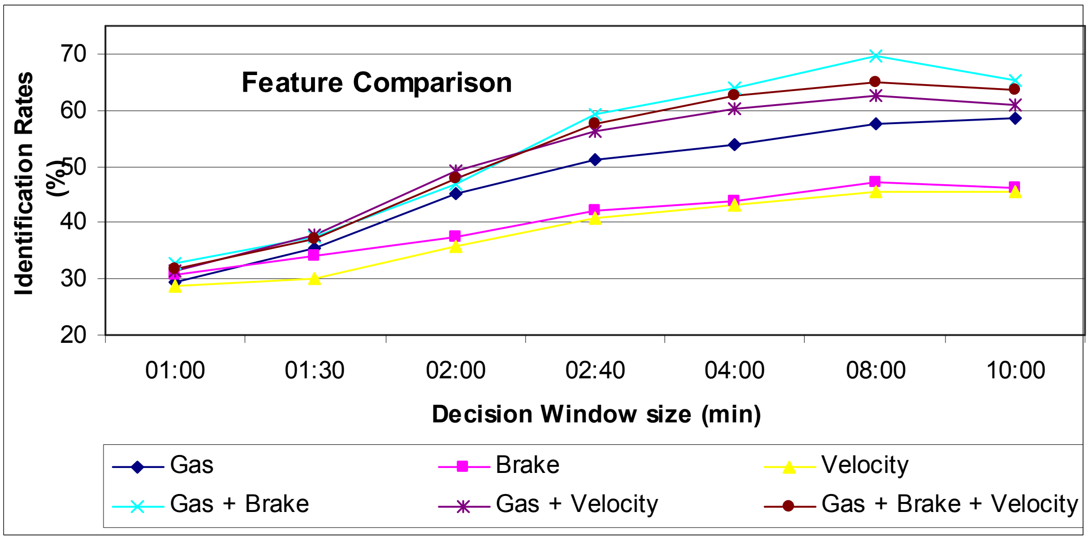


Fig. 4.5 Driver identification rate of GMM for combination of various driving signals

The identification rates of Japanese research were 81% for twelve drivers using a driving simulator and 73% for thirty drivers using an actual vehicle [16].

In a real-life scenario, typically a car is used by several drivers. Hence we investigate the performance of the driver identification system with reduced number of drivers. The dataset is divided into 3 groups, which are made up of 20 different subgroups including 3, 4 and 5 drivers respectively. The parameters we use in this experiment are 8 minutes of decision windows and 16 mixtures of GMMs, which have been observed to achieve better identification rates in the earlier experiments.

We employ the driver identification task for each subgroup by using 5-fold cross validation and evaluate an average identification rate for all 3 groups. Fig. 4.6 shows the average identification results for each group, using different features. We achieve 85.21% of success with the fusion of gas (G) and brake (B) pedal pressure signals among 3 drivers.

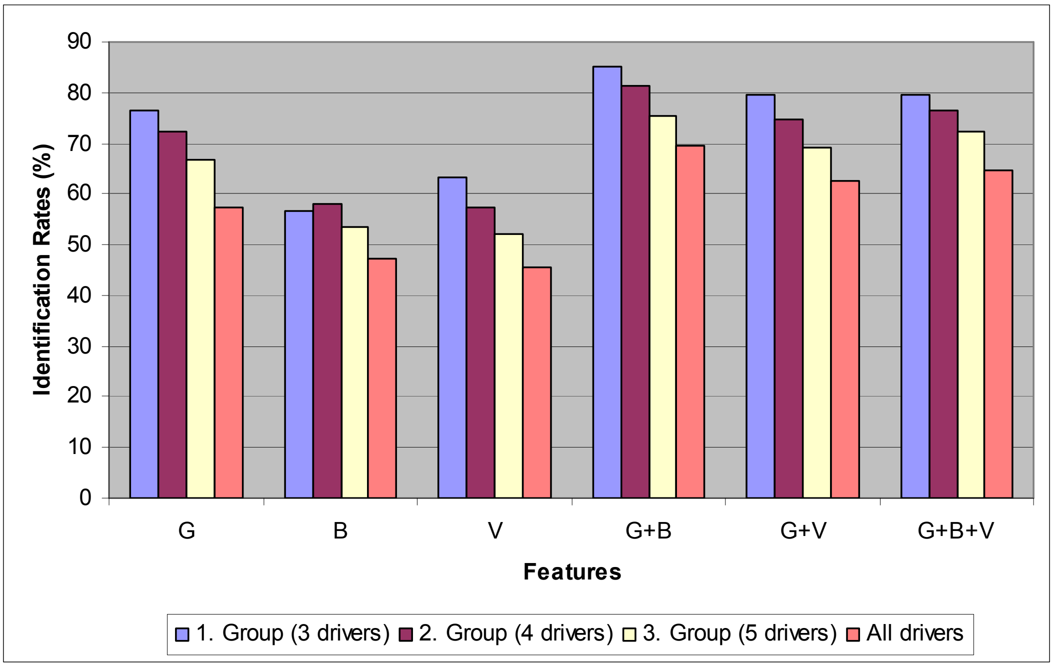


Fig. 4.6 Comparison of identification rates for different group of drivers

4.2. Driving status identification

In this study we also try to investigate the influence of the distraction conditions on driving performance and develop a technique for quantifying the stress level of drivers under various conditions with different tasks. In the UYANIK database nearly half of the driving sessions include driving under specific tasks. These tasks are dialog on cell phone, dialog with passenger and signboard reading, which are expected to cause lack of cognitive engagement in the driving task. The details of the tasks are described as follows:

- **No task**：A driver drives without any task.
- **Signboard reading**： A driver reads aloud the words on signboards/ plates during driving.
- **Dialogue on cellphone**：A driver goes to an unfamiliar place being guided by a navigator over cell-phones. Also online banking application is done over cell-phone.
- **Conversation with passenger**：A driver talks with the on board passenger.

In order to investigate the use of driving behavior signals to classify different driving tasks; we build a driving task identification system and perform identification performance analysis over the U-TASK database, which includes 10 drivers. For task identification purpose we use different decision window lengths and calculate features for every 1 second of frames. Features extracted for task identification purpose are entirely different from the features used for driver identification purpose, because it is not possible to obtain sufficient number of decision windows by using 3 sec. frame update interval in task identification as we do in driver identification.

Fig. 4.7 shows the histograms of the gas pedal pressure signal under different driving task conditions. Statistical differences between reference driving and driving under a task are clear. However, driving task specific histograms, especially dialog on cellphone and with passenger, are close to each other.

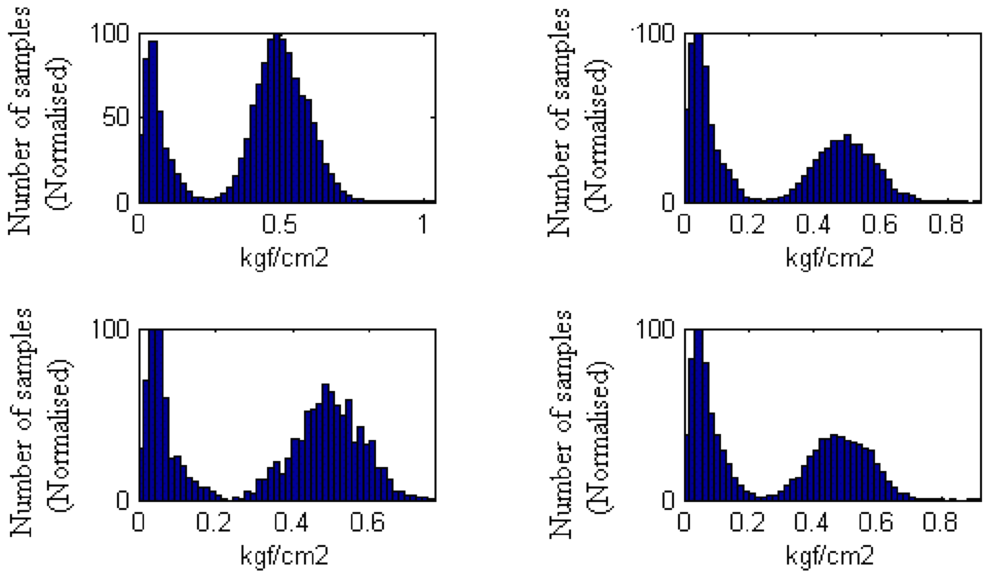


Fig. 4.7 Histograms of gas pedal pressure signals under reference driving (top left), dialog on cellphone (top right), signboard reading (bottom left) and dialog with passenger (bottom right)

We first consider a two-class classification system to identify reference driving and driving with a task. The two-class identification system is expected to show whether distractive conditions are influential on driving performance. Among 10 drivers' data reference driving last 190 minutes (47.8% of all data) and driving under a task last 207.5 minutes (52.2% of all data) totally. Each session is considered as a class independent from drivers. To evaluate task vs. no-task identification we use 16 Gaussian mixtures for constructing our model and 5-fold cross validation for classification. If everything is random performance rate is expected to be 50.1%.

The average identification rates of the classifiers using gas and brake pedal pressure signals and their decision fusion with different decision window sizes are given in Figure 4.8. The best scenario is achieved by using 360 seconds of decision windows.

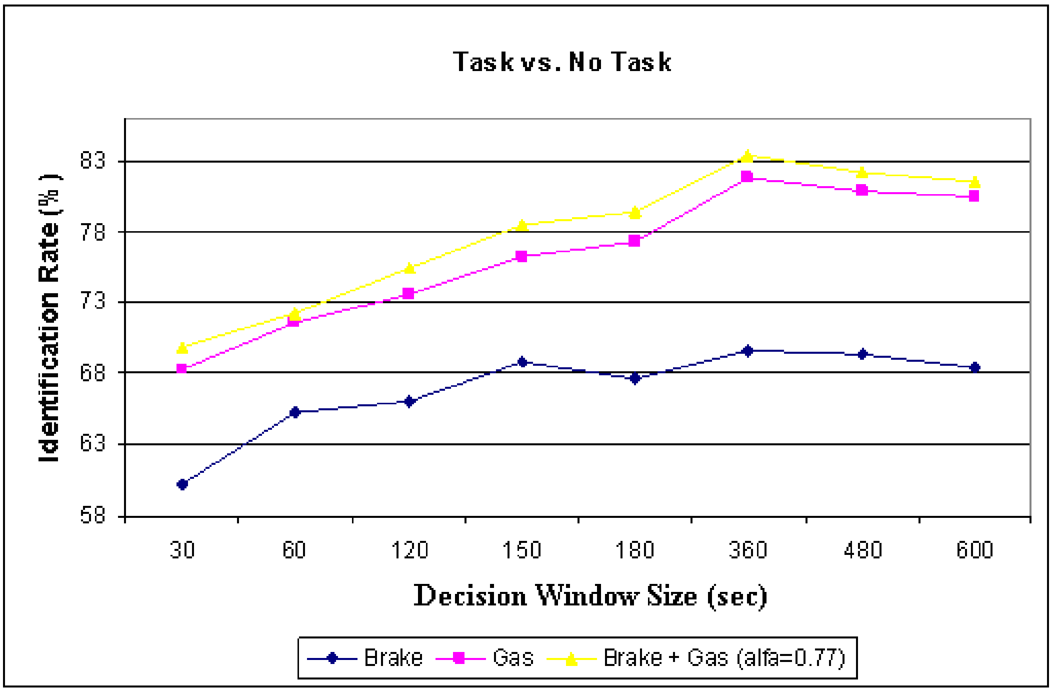


Fig. 4.8 Average identification rates of the classifiers using gas and brake pedal pressure signals and their decision fusion with different decision window sizes

Table 4.1 shows the identification rates of each class for this scenario. In this table, the last column presents the prior reference distribution of events in the database. We identify a reference driving session with 93.2% of success and identify a driving session under a specific task with 72.5% of success by using the fusion of gas and brake pedal signals. The average task vs no-task identification result is obtained as 83.3% with the fusion of 16 mixture GMM classifiers of gas and brake signals. Note that, these identification rates are significantly higher than random.

Table 4.1 Task vs no-task identification results of 16 mixture GMM classifiers with 360 sec decision windows (%)

	G	B	G+B	R
No-Task	91.1	76.6	93.2	52.2
Task	71.6	61.9	72.5	47.8
Avg.	81.8	69.6	83.3	50.1

We also consider identification of individual tasks from driving behavior signals. Among all driving sessions under a specific task dialog on cellphone lasts 97.5 minutes (47.56% of all driving with a task data), conversation with passenger lasts 87.5 minutes (42.68% of all driving with a task data) and signboard & license plate reading lasts 20 minutes (9.76% of all driving with a task data) totally. Each session under different tasks is considered as a class independent from drivers. To evaluate task identification we use 16 Gaussian mixtures for constructing our model and 5-fold cross validation for classification. If everything is random performance rate is expected to be 41.8%.

Task class dependent average identification results with reference prior distribution of task data is given in Figure 4.9. This figure shows that selecting window length is not crucial for this experiment.

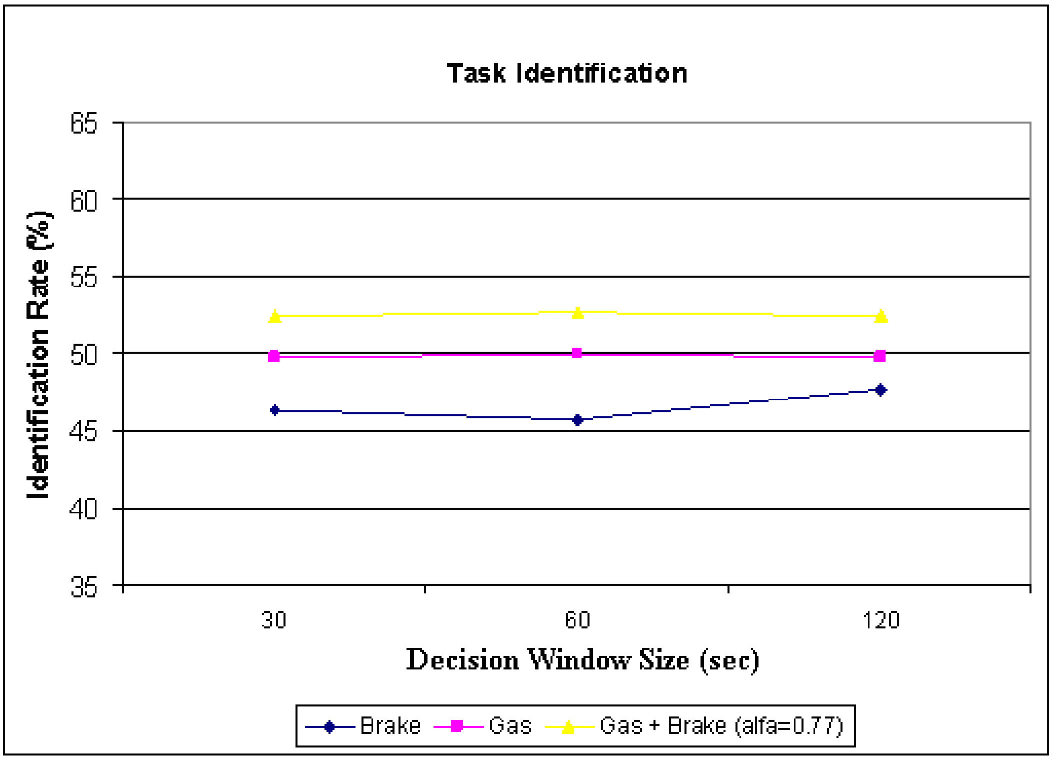


Fig. 4.9 Average task class dependent identification rates of the classifiers using gas and brake pedal pressure signals and their decision fusion with different decision window sizes

Table 4.2 shows the identification rates of each class for the best scenario. Dialog on cellphone task is identified with 58.5%, signboard reading with 25% and conversation with passenger with 52.6% of success by using the fusion of gas and brake pedal signals. The average task identification result is obtained as 52.7% with 60 sec. of decision windows and the fusion of 16 mixture GMM classifiers of gas and brake signals. Identification rates are observed to be slightly higher than random for all task classes.

Table 4.2 Task identification results of 16 mixture GMM classifiers with 60 sec decision windows (%)

	G	B	G+B	R
Dialog on cellphone	56.4	49.7	58.5	47.6
Signboard reading	17.5	32.5	25	9.7
Conversation with passenger	50.3	44.1	52.6	42.7
Avg.	50	45.7	52.7	41.8

4.3. Predicting Driver Behavior

We construct a driving behavior model to warn drivers about future incidents. A method of modeling driving behavior is concerned with certain period of past movements by using Hidden Markov Models in order to predict driver signals as described in Section 3.4. We use the U-DRIVER database for this purpose, which includes 23 drivers. Also we try to analyze the effects of cognitive distraction conditions on predicting driver behavior. For this purpose we benefit from the transcribed data, which is in the U-TASK database including 10 drivers. Here we apply 4-fold cross validation for all estimation experiments. This procedure is basically partitioning the signal into 4 parts, taking one as test data while keeping other segments for training purpose and applying the test procedure 4 times for each part. These parts are made up of equally numbered segments constructed by HMM clustering. Since the lengths of these segments are not equal, the ratio of test/training data over time is different for all drivers.

In this experiment we try to predict one of the driving behavior signals by using a window of past samples of all behavior signals. All behavior signals are decimated by 4 for this experiment. The features are extracted over 800 ms windows (25 samples) for every 96 ms frames (3 samples). First we build a temporal correlation between all three signals using HMM structure shown in Fig. 4.10. This structure is specified by the following parameters:

- Set of discrete states S [= S_i, $(i$=1,2,…,$M)$]
- a_{ij} : State transition probability ($i=1,2,\ldots,M; j=1,2,\ldots,M$)

where, M denotes the number of states [15]. Transition probabilities from one state to another are set equal initially and system starts with probability 1 at the first state.

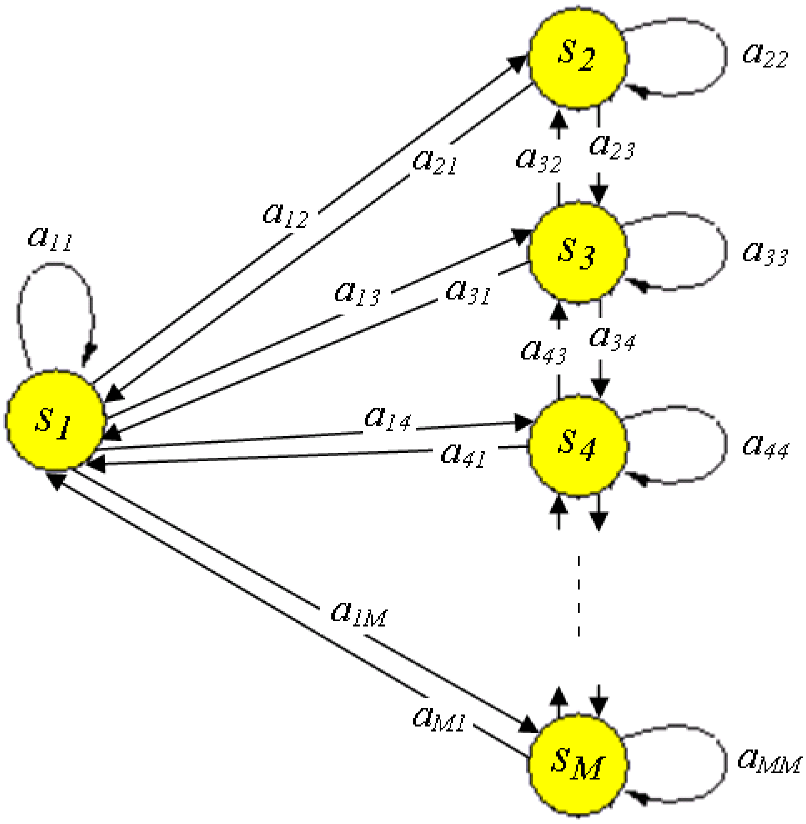


Fig. 4.10 HMM structure for clustering

The Viterbi decoding algorithm, explained in Section 3.4, determines the state sequence of the system as shown in Fig. 4.11. This is an example of HMM clustering by using 8 discrete states.

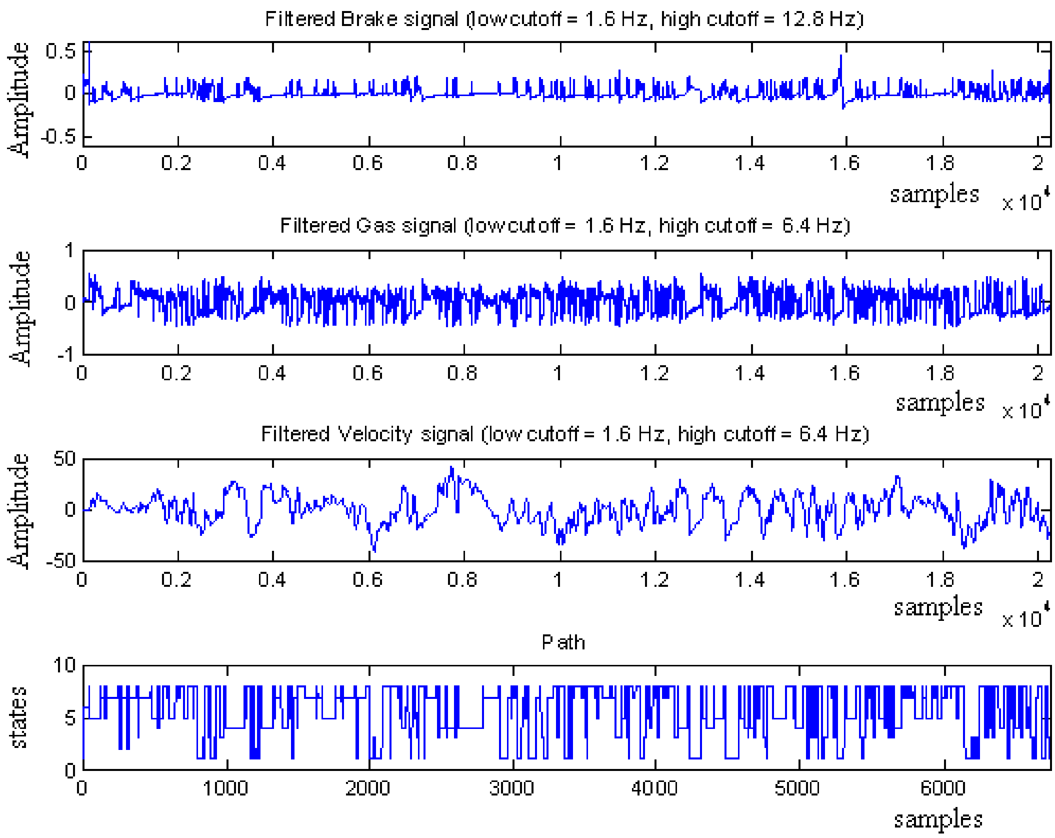


Fig. 4.11 State sequence of the system

In each segment, constructed by HMM clustering we perform a linear prediction analysis to estimate current driving behavior sample from N recent driving behavior samples. Our prediction method is described in Section 3.3. Here, it is important to select the appropriate linear prediction filter order. We observe correlation between current and recent driving behavior samples to decide it. Fig. 4.12 shows how this correlation changes considering the filter order. The y-axis shows the correlation of N recent samples of different behavior signals with the corresponding behavior signal (R_{yxi}). Here,

$$x_n = f_n - \bar{f} \tag{4.1}$$

where $\bar{f}$ is the mean vector of f_n sequence and f_n represents a vector containing all past samples of all 3 driving behavior signals.

$$f_n = [d(n-1), d(n-2), \ldots, d(n-i)] \tag{4.2}$$

where

$$d(n) = [b(n), g(n), v(n)] \tag{4.3}$$

In Fig. 4.12 x-axis shows the number of past samples used for each behavior signal (filter order). Also,

$$y = y_n - \bar{y} \tag{4.4}$$

where, y_n represents the sample to be estimated and $\bar{y}$ is the mean of the driving behavior sample, which the sample y_n is element of at current state. In Fig. 4.12 y denotes the (a) brake, (b) gas and (c) velocity signals respectively. R_{yx} is calculated as:

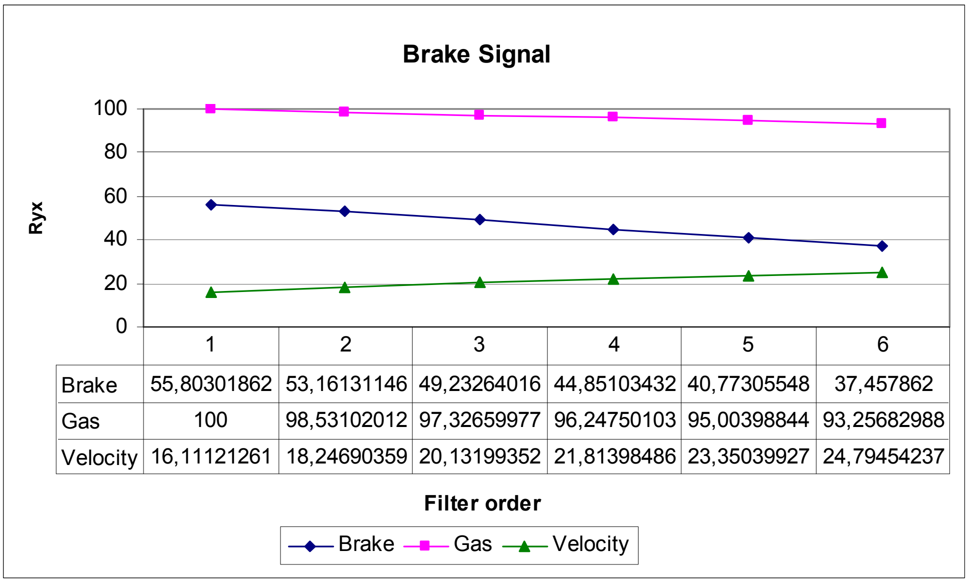
$$R_{yx} = \begin{bmatrix} R_{yx0} \\ R_{yx1} \\ \vdots \\ R_{yxp-1} \end{bmatrix} \tag{4.5}$$

Here R_{yx_i} is calculated as:

$$R_{yx_i} = \frac{1}{M} \frac{\sum_{i=1}^{M} y^i x^i}{\sqrt{\sum_{i=1}^{M} x^i x^i \sum_{i=1}^{M} y^i y^i}} \tag{4.6}$$

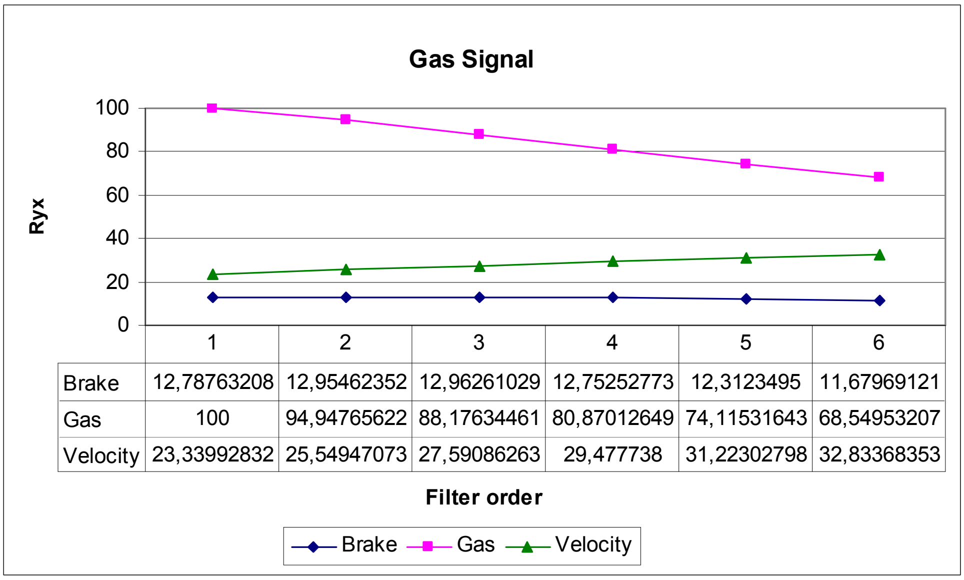
where M is the number of samples at the current segment.

Values are normalized to 0-100 interval. In Fig. 4.12 it is clear that taking 6 samples from velocity signal and 1 sample from pedal operation signals would yield us better prediction results.



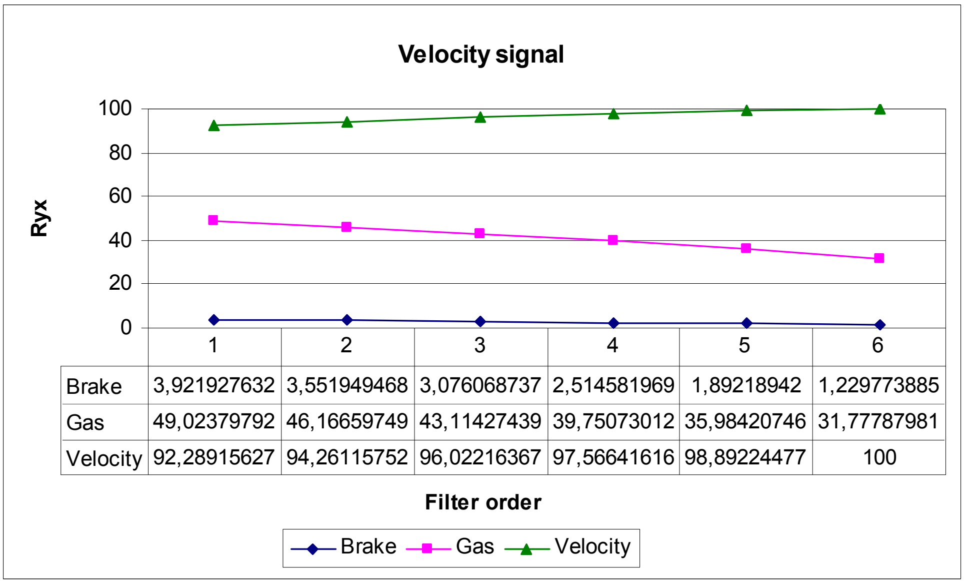
	1	2	3	4	5	6
Brake	55,80301862	53,16131146	49,23264016	44,85103432	40,77305548	37,457862
Gas	100	98,53102012	97,32659977	96,24750103	95,00398844	93,25682988
Velocity	16,11121261	18,24690359	20,13199352	21,81398486	23,35039927	24,79454237

(a)



	1	2	3	4	5	6
Brake	12,78763208	12,95462352	12,96261029	12,75252773	12,3123495	11,67969121
Gas	100	94,94765622	88,17634461	80,87012649	74,11531643	68,54953207
Velocity	23,33992832	25,54947073	27,59086263	29,477738	31,22302798	32,83368353

(b)

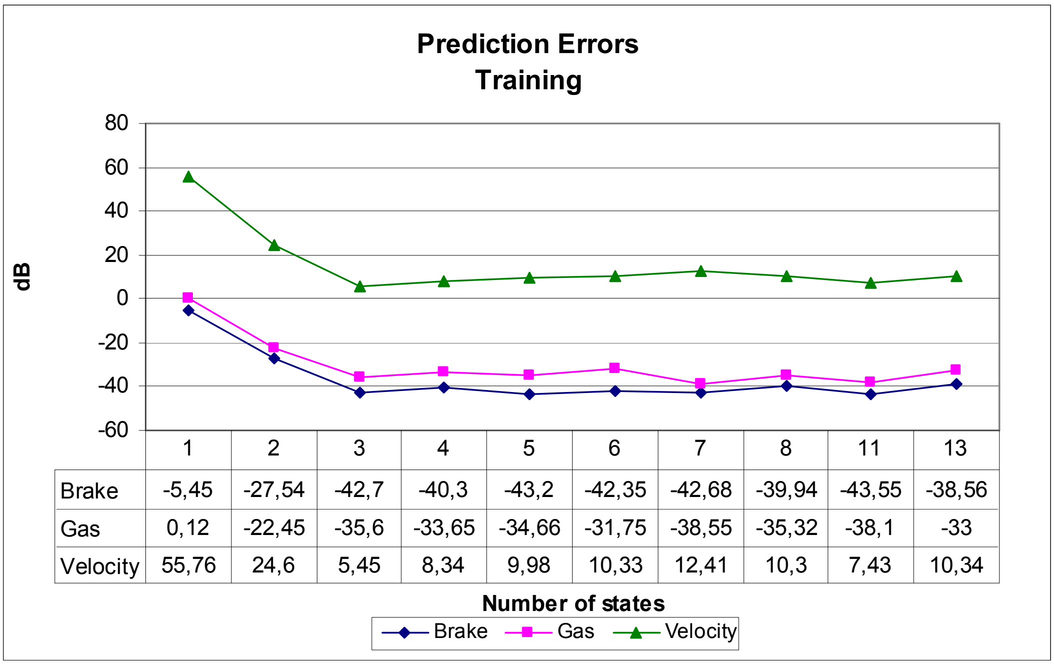


	1	2	3	4	5	6
Brake	3,921927632	3,551949468	3,076068737	2,514581969	1,89218942	1,229773885
Gas	49,02379792	46,16659749	43,11427439	39,75073012	35,98420746	31,77787981
Velocity	92,28915627	94,26115752	96,02216367	97,56641616	98,89224477	100

(c)

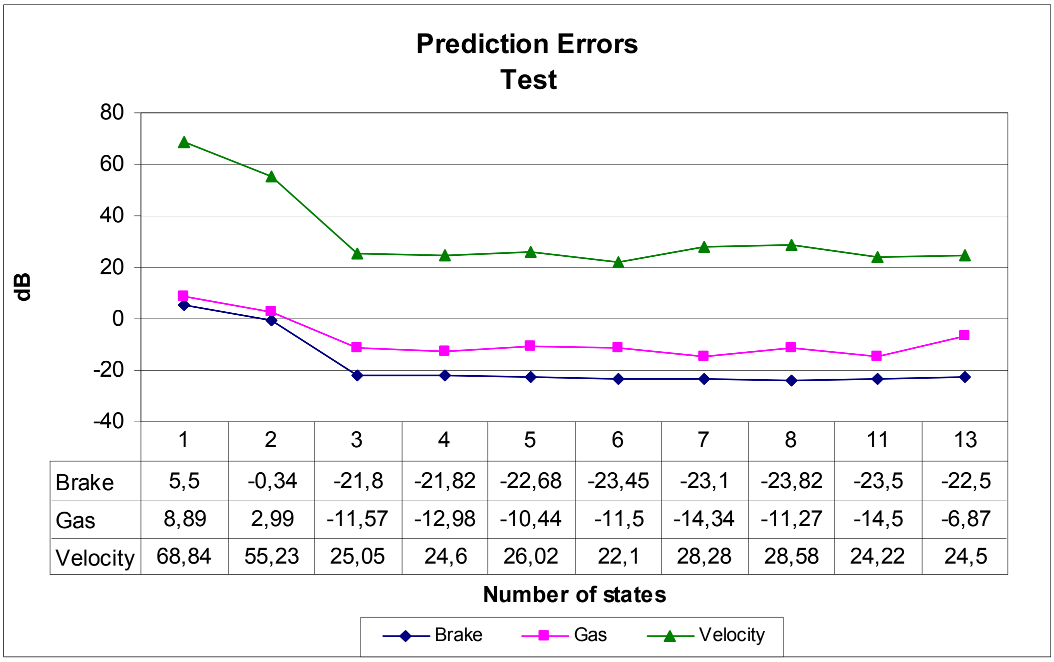
Fig. 4.12 Correlation between current (a) brake signal, (b) gas signal, (c) velocity signal and recent driving behavior samples

After selecting the filter order we need to decide the number of states for HMM clustering. To do so, we try different number of states and calculate the mean squares error for each case. Fig. 4.13 and Fig. 4.14 show how the error changes depending on the state number for training and test data respectively. The 3 state HMM structure is chosen as an adequate model for the classification of driving behavior signals.



	1	2	3	4	5	6	7	8	11	13
Brake	-5,45	-27,54	-42,7	-40,3	-43,2	-42,35	-42,68	-39,94	-43,55	-38,56
Gas	0,12	-22,45	-35,6	-33,65	-34,66	-31,75	-38,55	-35,32	-38,1	-33
Velocity	55,76	24,6	5,45	8,34	9,98	10,33	12,41	10,3	7,43	10,34

Fig. 4.13 Prediction errors for training data



	1	2	3	4	5	6	7	8	11	13
Brake	5,5	-0,34	-21,8	-21,82	-22,68	-23,45	-23,1	-23,82	-23,5	-22,5
Gas	8,89	2,99	-11,57	-12,98	-10,44	-11,5	-14,34	-11,27	-14,5	-6,87
Velocity	68,84	55,23	25,05	24,6	26,02	22,1	28,28	28,58	24,22	24,5

Fig. 4.14 Prediction errors for test data

For the selected linear prediction filter order (taking 6 samples from velocity, 1 sample from gas and 1 sample from brake signal) and 3 HMM states, we estimate driving behavior samples in 2 scenarios:

In the first scenario we use the direct samples of behavior signals at each prediction step. We construct the feature vector $d(n) = [b(n), g(n), v(n)]$ where *b, g* and *v* vectors denote the raw samples taken from brake pedal pressure signal, gas pedal pressure signal and velocity signal of the corresponding segment respectively and use the following method to predict the behavior signal:

$$\hat{s}(n) = P([d(n-1), d(n-2), \dots, d(n-i)]) \tag{4.7}$$

where $\hat{s}(n)$ is the sample to be estimated and i is the number of past samples used.

Fig. 4.15 shows the prediction steps for this scenario. Here, points in blue represent the raw samples and green ones represent the sample to be estimated. Points in red circles are used as past samples for predicting the green points. At each step we use the raw samples to predict the behavior samples.

Driving behavior samples are estimated as shown in Fig. 4.16 for one randomly selected driver by using this scenario. Here, signal plotted in blue represents the actual signal and the red one represents the estimated signal.

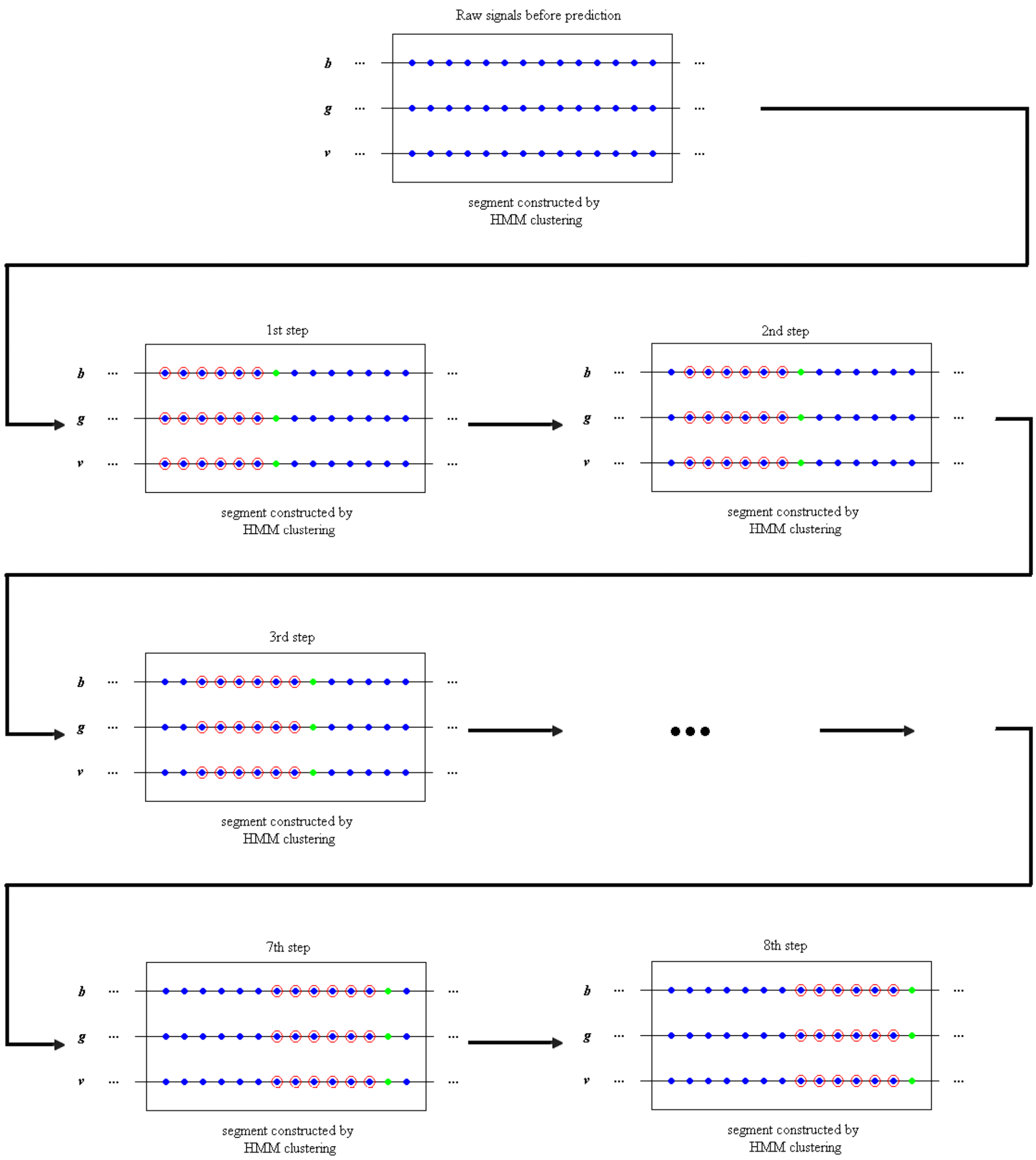


Fig. 4.15 Prediction steps for the first prediction scenario

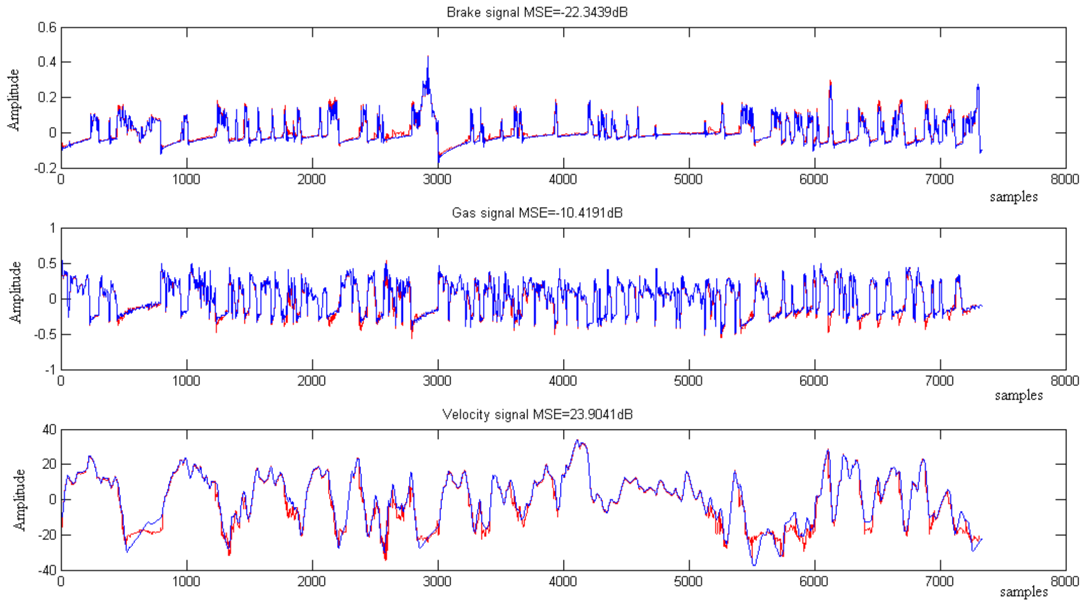


Fig. 4.16 Driving behavior signal estimation for the first prediction scenario

In the first scenario we assume that all raw samples in the corresponding segment are available. If we know all samples, prediction process is meaningless. So we consider another scenario assuming that only a few samples are available.

Second scenario is briefly updating the direct samples with the estimated ones at each step. We construct the feature vector $d(n)=[b(n),g(n),v(n)]$ and use the following method to predict the behavior signal:

$$\hat{s}(n)=P(\left[\tilde{d}(n-1),\tilde{d}(n-2),...,\tilde{d}(n-i)\right]) \tag{4.8}$$

where $\hat{s}(n)$ is the sample to be estimated, $\tilde{d}(n)$ is a vector containing estimated samples of brake, gas, velocity signals and i is the number of past samples used. For the first 6 steps if a sample hasn't been estimated, we use the raw samples instead.

Fig. 4.17 shows the prediction steps for this scenario. Here, points in red represent the estimated samples, blue points represent the raw samples and green ones represent the sample to be estimated. Points in red circles are used as past samples for predicting the green points.

Driving behavior samples are estimated as shown in Fig. 4.18 for one randomly selected driver by using the second scenario. Here, signal plotted in blue represents the actual signal and the red one represents the estimated signal.

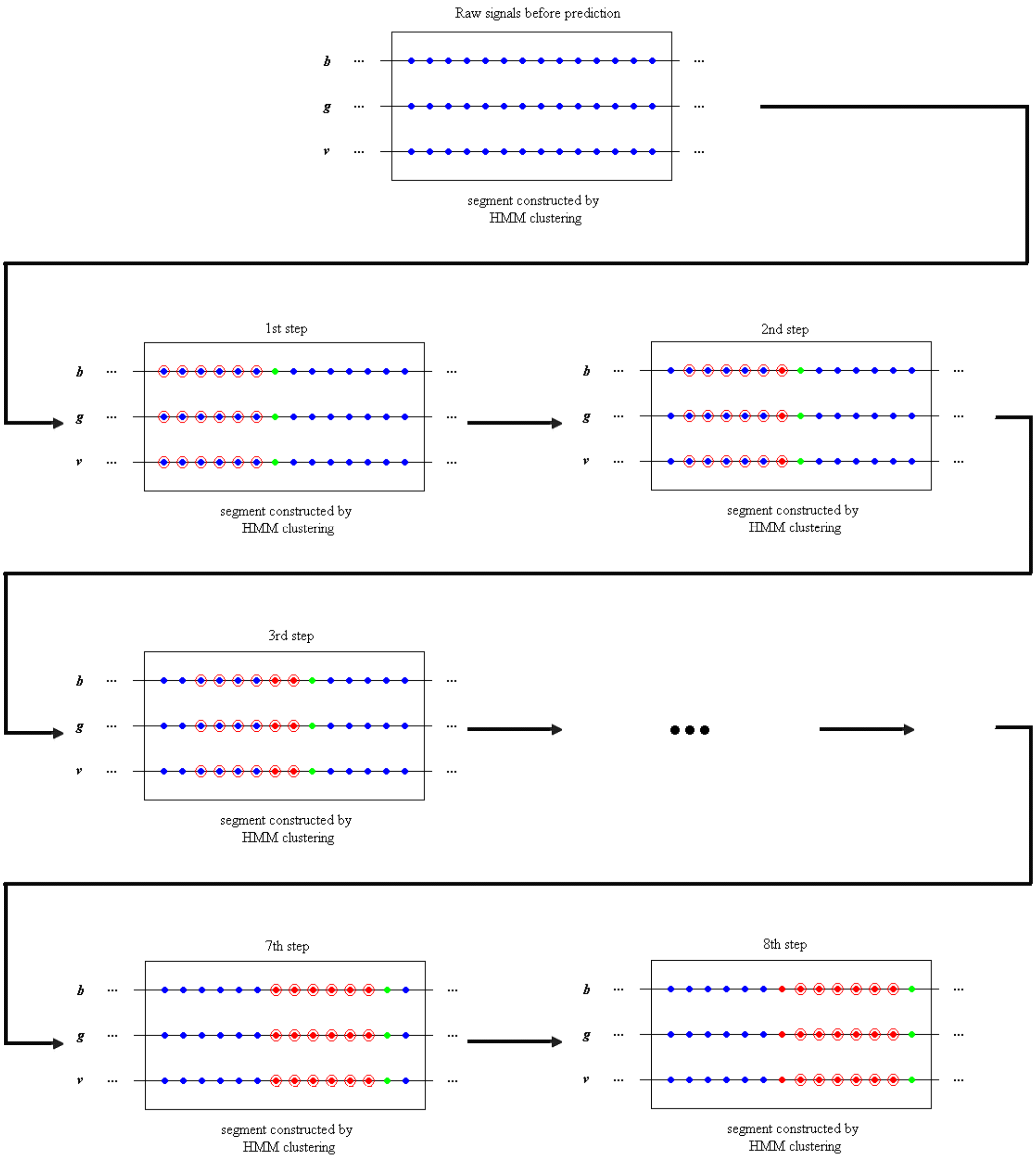


Fig. 4.17 Driving behavior signal estimation for the second prediction scenario

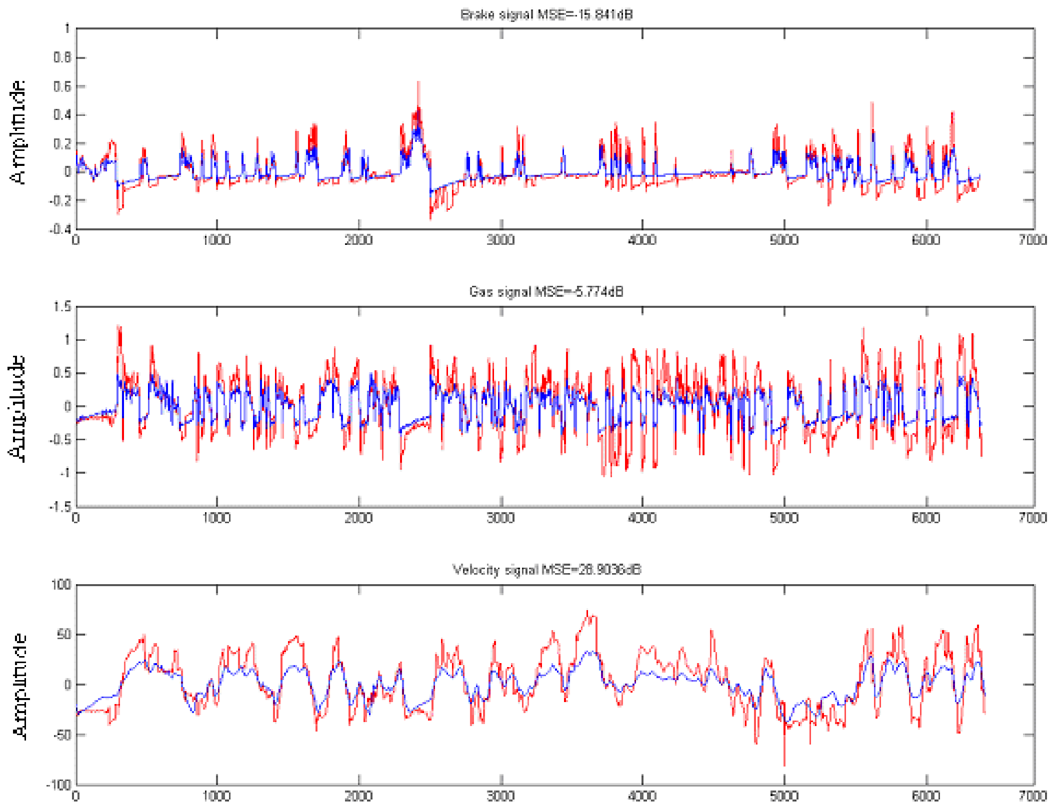


Fig. 4.18 Driving behavior signal estimation for the second prediction scenario

We also apply this method for driver independent experiment. Among the database we select 20 drivers for training and the remaining 3 drivers for testing. Test data for each 3 driver is same with the one that we used in driver dependent experiment. In both driver dependent and independent experiments parameters are set all equal. Clustering is done with the structure shown in Fig 4.10 by using 3 HMM states and in the prediction process we use 6 past samples from velocity, 1 sample from gas and 1 sample from brake signal to predict the next behavior sample. We apply our prediction method (second scenario) for each test driver and calculate an average prediction error. Fig. 4.19 shows the prediction errors for driver independent experiment with comparison to driver dependent one. Considering these results prediction driver behavior in driver independent experiments is more difficult than driver dependent experiments.

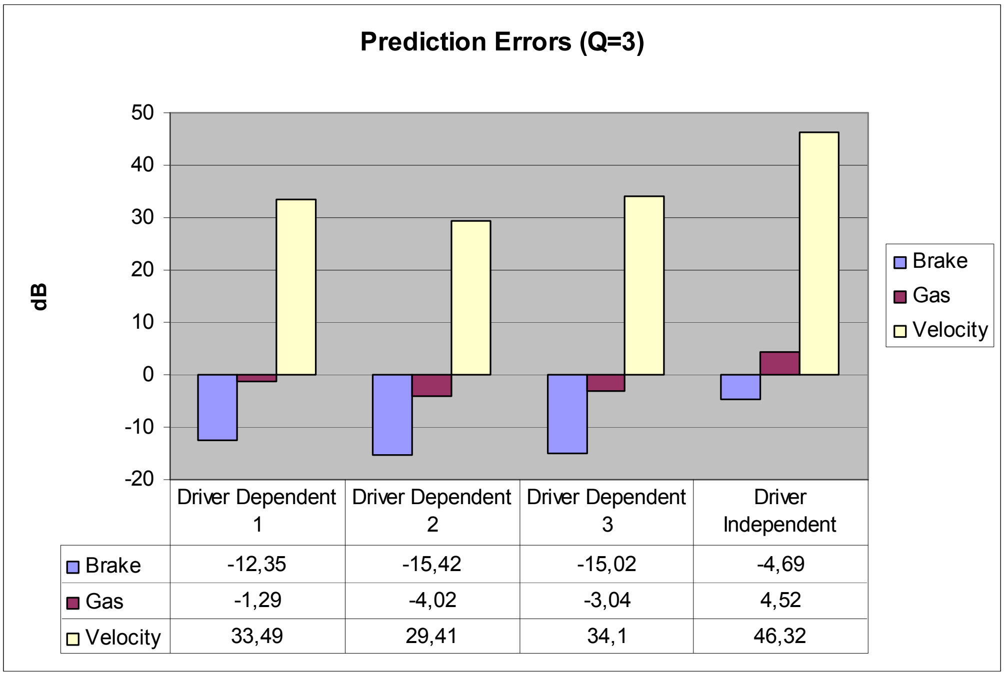


Fig. 4.19 Prediction errors for driver independent experiment with comparison to driver dependent one

We evaluate the prediction errors for each sample of behavior signals regarding to one randomly selected driver and plot its graph via all samples as shown in Fig. 4.20. In Fig. 4.20 some segments contain high level of prediction errors. To investigate the driving conditions where these errors appear, it is necessary to determine and transcribe high erroneous parts clearly. To do so, we select the 20% of the highest prediction error as the threshold value and define the segments higher than this threshold as high erroneous parts.

To figure out the effects of driving conditions on prediction we calculate the ratio of change of length of driving tasks and road types over erroneous parts to the original amount over all parts. Percents of changes are shown in Fig. 4.21 and Fig. 4.22

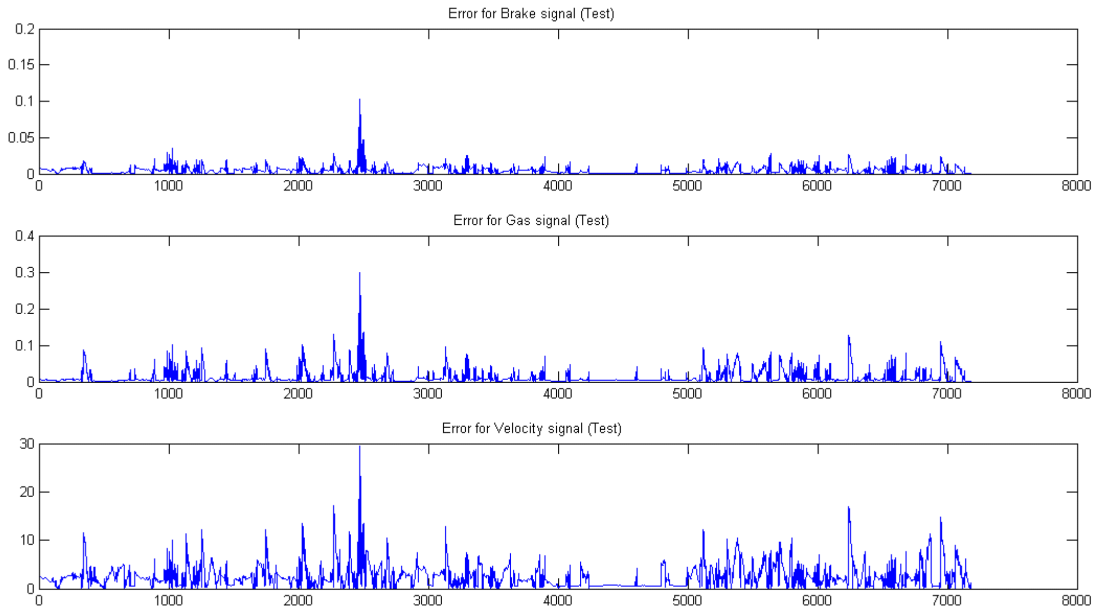


Fig. 4.20 Prediction errors for one driver's behavior signals

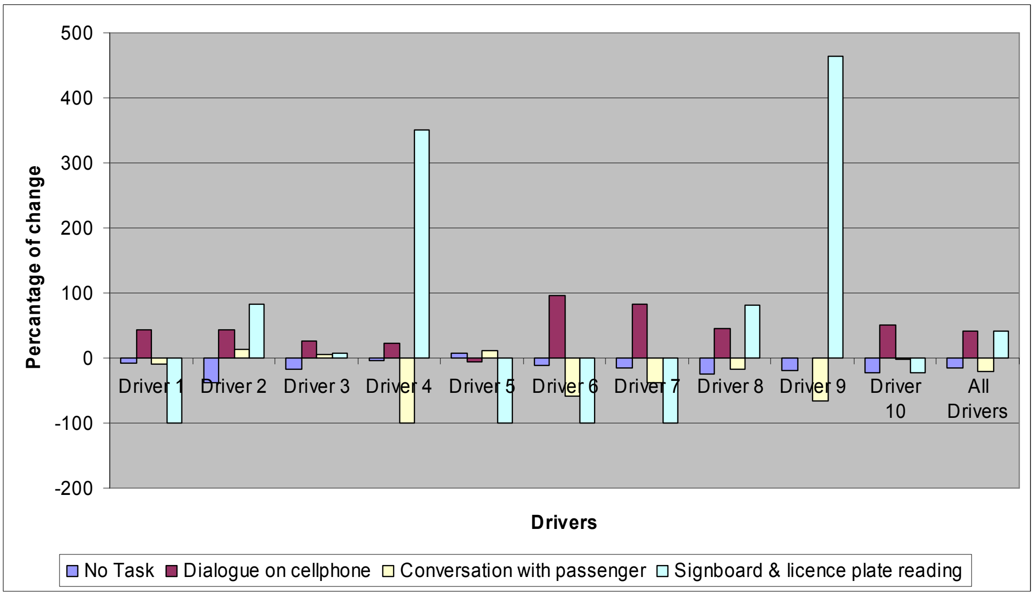


Fig. 4.21 Percentage of change of driving task lengths over erroneous parts for each driver to entire sessions

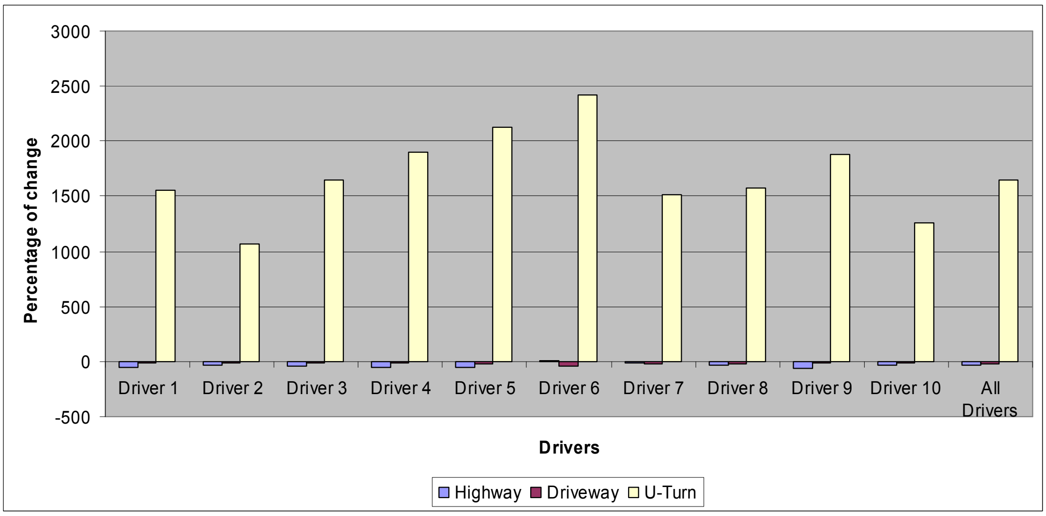
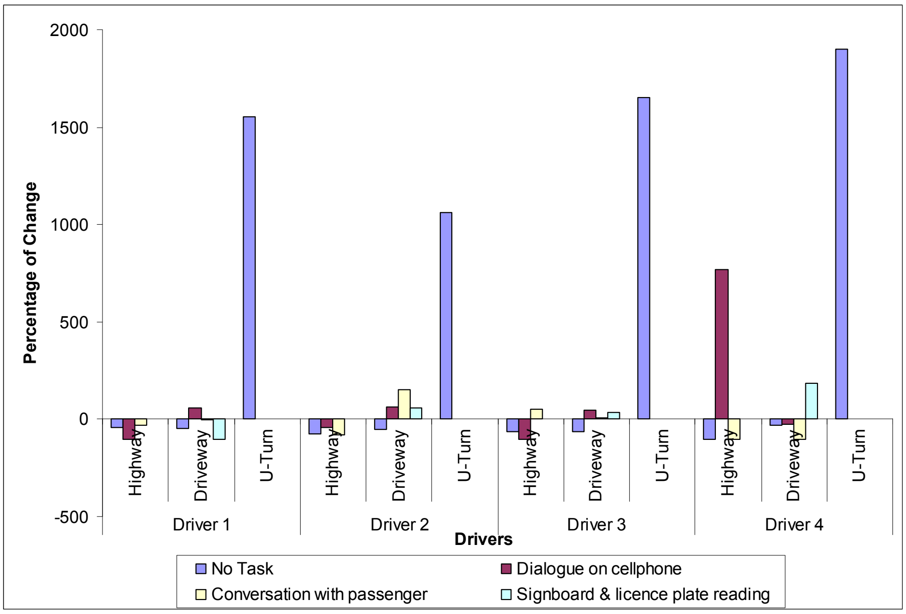
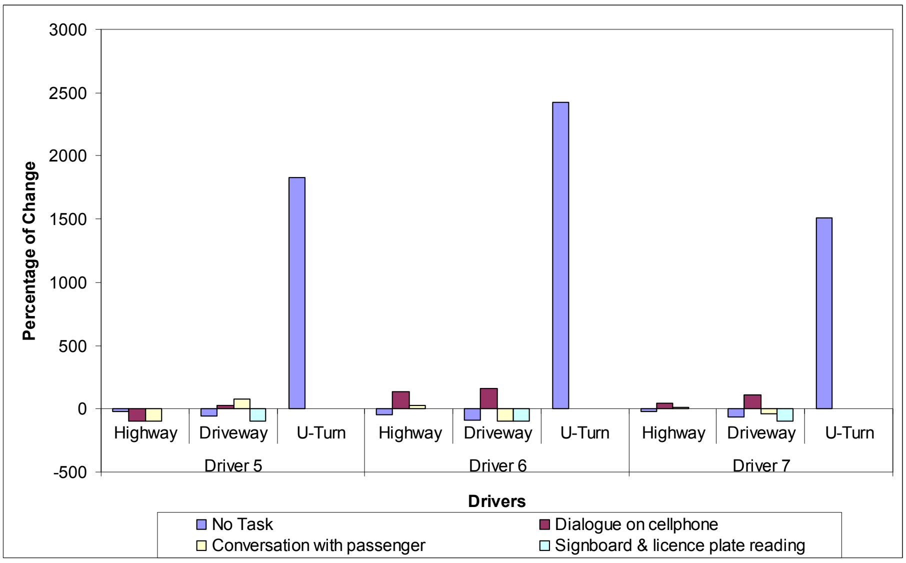


Fig. 4.22 Percentage of change of driving session lengths on different types of roads over erroneous parts for each driver to entire sessions

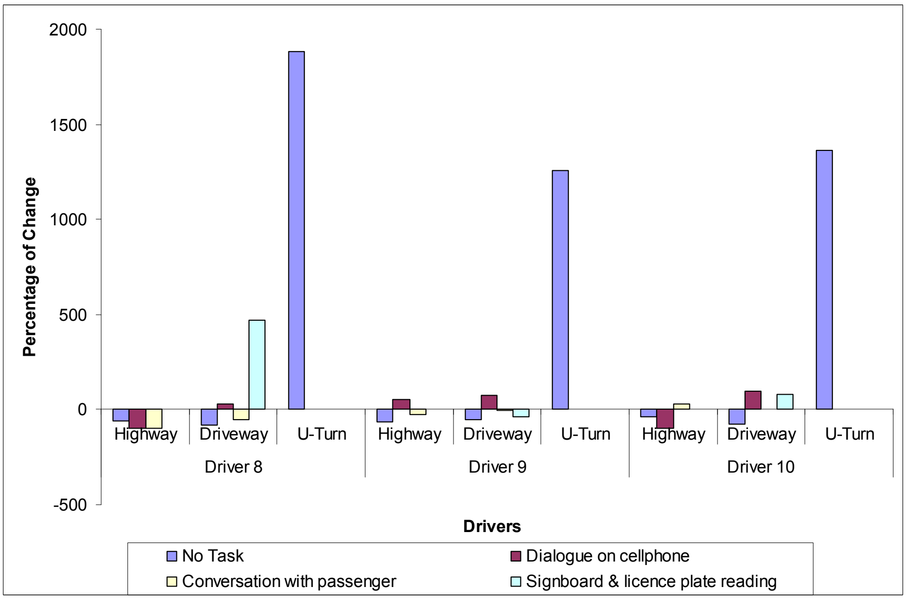
Considering Fig. 4.21 we can come to a conclusion that distractive conditions have a certain effect on driving behavior. Prediction of behavior signals under distractive conditions is more erroneous than prediction under no secondary task. Experiments show that the ratio of all task lengths over erroneous parts is slightly higher than the ratio of all task lengths over all segments. Fig. 4.21 also shows that among driving tasks dialog on cellphone is more effective on driving behavior than other tasks. Fig. 4.22 shows that road conditions are also effective on predicting driver behavior. It is hard to predict driver behavior on U-Turns, the connection part of highway and drive way. Sudden maneuvers and unsteady use of pedal operations may avoid predicting the next action. Percentage of change of driving task lengths on different road types over erroneous parts for each driver is summarized in Fig. 4.23.



(a)



(b)



(c)

Fig. 4.23 . Percentage of change of driving task lengths on different road types over erroneous parts for each driver with comparison to entire sessions

CHAPTER 5

CONCLUSION

In this thesis we consider the problem of driver and driver status identification under different cognitive stress/distraction conditions. Also we try to predict driving behavior signals by using the past movements of the drivers. Our objective is to construct a system to facilitate driver-vehicle interaction by analyzing the driving behaviors. To study and determine the nature of driving behavior we benefit from the characteristic driving signals including brake pedal pressure, gas pedal pressure, vehicle velocity and the distance from the vehicle in front signals. The system is expected to be more reliable due to the presence of sufficient amount of driving behavior signals.

We collaborate with the Drive Safe Consortium in Turkey. Driving behavior data was collected by a test vehicle, UYANIK, customized with various sensors, cameras, microphones and lasers with similar to other test vehicles used in USA and Japan. Among the collected database we benefit from 23 drivers' data for driver identification and driver behavior signal prediction experiments and 10 drivers' data for task identification purpose. Second subset of the database is also used to analyze the effects of distractive conditions on driver behavior estimation. All drivers drove the car on driveway and two-way, where they have to face with traffic congestion and also on highway with much less traffic. Their task is a 40 minutes of car driving under cognitive distraction conditions such as dialogue on mobile phone, conversation with passenger on board, sign reading and license plate reading. We rearrange 10 drivers' data sets via transcription for these tasks. For all experiments we use the gas, brake pedal pressure and vehicle velocity, which are the most beneficial ones for our study, among driving behavior signals. Also, we analyze the performance of the distance from the vehicle in front signal for the driver identification experiment.

To perform the feature extraction, we use the Cepstrum method. Cepstral analysis is a known source/filter separation method, which is defined as the inverse Fourier transform of the short-term log-power spectrum. In earlier studies the cepstrum method has been applied to the driving behavior signals [4]. When the driving behavior signals are modeled as outcomes of a system which is excited by commands of driver, cepstral analysis yields a fine spectral representation of the system. Also, same studies have shown that probabilistically sophisticated Gaussian Mixture Models would better suit for our purposes as a training algorithm.

Driver behavior signals are modeled with Gaussian Mixture Models that represent spectral characteristics extracted. In driver identification experiment, test results show that decision fusion method significantly increases our system performance. We achieve 69.5% of success with the fusion of gas and brake pedal pressure signals, while these signals can reach 58% of success at most individually among 23 drivers. Driver identification results of the car following task is lower than the pedal operation models however it is feasible to use them to recognize a driver. Since the pedals are operated directly by the driver, they yield us the best feature to identify the driver characteristics. We also apply the same identification method on a group of few drivers to achieve more realistic results. The best identification result is obtained as 85.21% with the fusion of gas and brake pedal pressure signals among 3 drivers by using 16 mixtures of GMM and 8 minutes of decision windows, which have been proved to achieve higher performance rates in the earlier experiments.

In this study we also try to develop a distraction detection module based on driving behavior signals. Distraction detection is an important issue because cognitive/stress conditions have a great influence on driving behavior. We achieve 93.2% of success in detecting the driver behavior signals under no specific task while the random rate is about 52% among 10 drivers. In our database nearly half of the driving sessions are done under specific task. Among these tasks dialog on mobile phone, conversation with passenger on board, sign reading and license plate reading are the most effective ones. We evaluate identification rates of these tasks individually and observe that these rates are slightly higher than random values. Because of time and computational constraints we can only transcribe 10 drivers' datasets. The results suggest that relatively more efficient transcription methods could yield better performance rates on more drivers' data.

Warning drivers about future incidents is an important application area because many of the traffic accidents are caused by drivers. In this study we propose a method of predicting driving behavior based on gas pedal pressure, brake pedal pressure and vehicle velocity signals. These behavior signals are employed for our model with Hidden Markov Models. Estimation method is concerned with past driving movements since human's behavior is strongly related to past actions. Preliminary findings show us that 3 states of HMM, 6 past samples of velocity and 1 past sample of each pedal operation signals are adequate for our purpose. Predicting a single sample by using past samples yield us encouraging results while predicting more than one sample fails to achieve our aim. We did this experiment on both dependent and independent of drivers. Considering the results we can come to a conclusion that though prediction errors for driver independent experiment is slightly higher than the driver dependent one, drivers' behavior can be predicted by using other drivers' samples with sufficient error rates. Earlier findings have shown us that distractive conditions have a great influence on driving behavior. Prediction results are also supporting this finding. Prediction of driving behavior signals under distractive conditions is 20% more erroneous than prediction under no secondary task. Also road conditions are influential on predicting samples.

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