# Active vehicle safety system design based on driver characteristics and behaviour

Pinar Boyraz* and John H.L. Hansen

Erik Jonsson School of Engineering and Computer Science,
Electrical Engineering Department,
The University of Texas at Dallas,
Richardson, TX 75080, USA
E-mail: boyraz.pinar@googlemail.com
E-mail: john.hansen@utdallas.edu
*Corresponding author

**Abstract:** In the development of driver adaptive and context aware active safety applications, driver–vehicle interaction signals offer excellent opportunities for advanced system design, yet limited progress has been realised. The implementation of driver adaptive and context aware systems requires longer time windows to analyse the current status of the driver and/or traffic situation ahead. In this study, a summary of systems that can be realised based on the long-term analysis of driver–vehicle interaction signals is presented. These signals are readily obtained by using Controller Area Network (CAN) Bus via On Board Diagnostic System (OBD) II port that can be utilised at low cost. Based on the analysis results, quantitative metrics are suggested that can be used in many ways, with two prospects considered here: (1) manoeuvres can be recognised for context aware intelligent active safety and (2) the models or signal processing methods can be proposed so as to distinguish distracted/impaired driver behaviour from normal/safe behaviour.

**Keywords:** AVS; active vehicle safety; intelligent vehicle systems; signal processing; driver behaviour modelling.

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## 1 Introduction

The last 20 years have witnessed a transformation of modern automobiles, turning them into vehicles packed with sensors, micro-chips and actuators, all forming integrated and modular sub-systems of safety, infotainment and energy management. In fact, it is reasonable to say that automobiles are the first merged domain of mechanical and electrical/electronic components offering flexibility for better control of

1 energy production and use (i.e. timed/controlled internal combustion engine cycle or hybrid technology energy cycle/system switch management)

2 vehicle dynamics (i.e. ABS, ESP)

3 instrument cluster (i.e. better displays, adaptable controls, setting points, etc.)

4 driver assistance systems (i.e. lane keeping, adaptive cruise control, blind spot warning, parking assistance, etc.).

At the centre of these developments is a protocol that makes it possible to communicate messages between sensors, processing units and actuators. That protocol was called Controller Area Network (CAN)-Bus introduced in the early 1990s by Bosch, Germany (1991). While this transformation has been taking place, other dimensions have caught the attention of researchers. All technology in modern vehicles must also consider the human component: driver. Although, the pursuit of understanding or modelling human driver behaviour is not new as can be seen in McRuer and Weir (1969), Pilutti and Ulsoy (1999), Nechyba and Xu (1998), Yang et al. (1997) and Salvucci (2006) the long-awaited unification between advanced vehicle concepts and human-centred systems has just begun. To be able to design truly cooperative and effective driver assistance, safety or infotainment systems, driver behaviour needs to be better understood, modelled and incorporated into overall system design. The focus of this study is to utilise some of the driver–vehicle interaction signals available from CAN-Bus and demonstrate new opportunities of developing more advanced driver assistance using CAN-Bus in a novel way. The final point in this study is the demonstration of potential impacts of several driver monitoring applications which use several other information sources (i.e. video, audio and bio-signals) based on real accident data.

## 2 Framework and methodology

To design active vehicle systems operating in a preventative way, it is crucial to take the driver, vehicle and environment dynamics into account. Driver dynamics can be expanded into several aspects including response time, general characteristics, capabilities and performance metrics. Environment dynamics are mostly related to the current traffic flow information and neighbouring vehicles, pedestrians and a range of road objects. Given the driver and environment dynamics, a contextual baseline model for the expected manoeuvres and driver response can be constructed. Acquiring such information and developing the corresponding model can help preventative systems to act in a responsive manner to avoid accidents 90% of which are caused by human errors Salvucci (2006). It should be also noted that not all accidents can be prevented since the timeline of the accident sequence combined with the physical limitation of vehicle systems render it impossible to avoid some situations. In those cases, a mitigation strategy can be employed to reduce the impact of inevitable accidents. There are challenges to overcome in order to obtain a reliable model as a baseline or reference to identify abnormal pre-events or indicators before an incident takes place. Some of these challenges are as follows:

- *Measurement*: Most driver dynamics are difficult to quantify, and are usually obtained in a qualitative manner. Therefore, fundamental research is needed to generate a list of candidate quantitative metrics to characterise and probe driver dynamics.
- *Complexity*: If a complete map of driver and environment dynamics are needed at any time instant, a multisensory system is necessary including cameras to monitor the road scene and driver, radar or laser-based systems for distance measurements, CAN-Bus for vehicle dynamics, and sensors to measure any physiological changes in the driver.
- *Time latency*: Although a multi-sensor approach is the right answer, it is often difficult to process single channels and combine such information in a reasonable time so that the output can be used by the safety system for prevention.
- *Reliability*: Most sensor technology is in a set of constant improvement and some specific channels may not be operating as expected due to challenges on board (i.e. computer vision systems are subjected to illumination change and vibration). Therefore, a multi-sensor system which can reconfigure itself based on the available channels may guarantee overall system reliability.
- *Cost*: As the system sensor count increases, the operating the cost of the system also increases. Any additional cost to the system needs to be justified adequately, that the utility ratio (potential savings in lives/cost) can be maximised for an active safety solution.

The ultimate aim in active vehicle safety (AVS) research and development is to overcome these challenges designing a multisensory system such as the conceptual system illustrated in Figure 1.

The prospective sensors are mapped into three domains as shown in the monitoring system in Figure 2. In this study, only a CAN-Bus-based system will be implemented in a systematic approach. The reason behind this focus is that the most important driver–vehicle interaction signals from CAN-Bus are already available in any vehicle and can be tapped using the OBD-II port, which holds the promise of a low-cost system. In addition, these signals are the most relevant in understanding driver and vehicle dynamics together (as depicted in Figure 2) since they represent their interaction. The third dimension of the problem, namely environment dynamics, deserves a detailed separate study, and therefore will not be addressed here.

Here, a systematic approach to signal processing for driver–vehicle interaction will be framed, applied and evaluated as a first step towards realising AVS systems with a predictive and/or monitoring attribute. It should be emphasised that only a part of CAN-Bus signals representing driver–vehicle interaction is used in this study having SWA and speed as the primary signal channels. The additional sensor channels are used to construct the ground truth and perform the labelling as detailed in Section 3.

**Figure 1** Conceptual multi-sensor system and block diagram for AVS

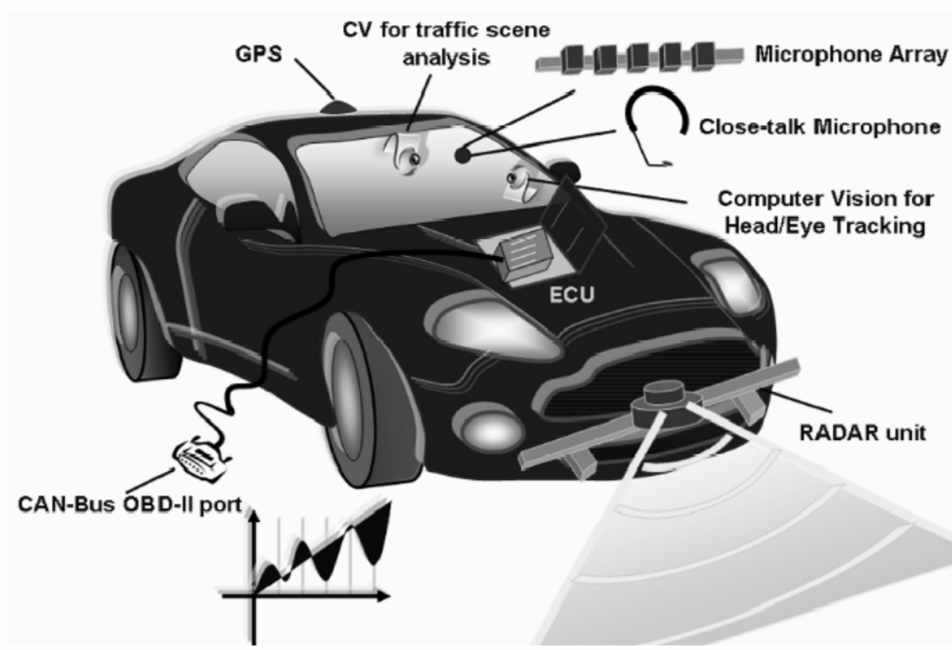
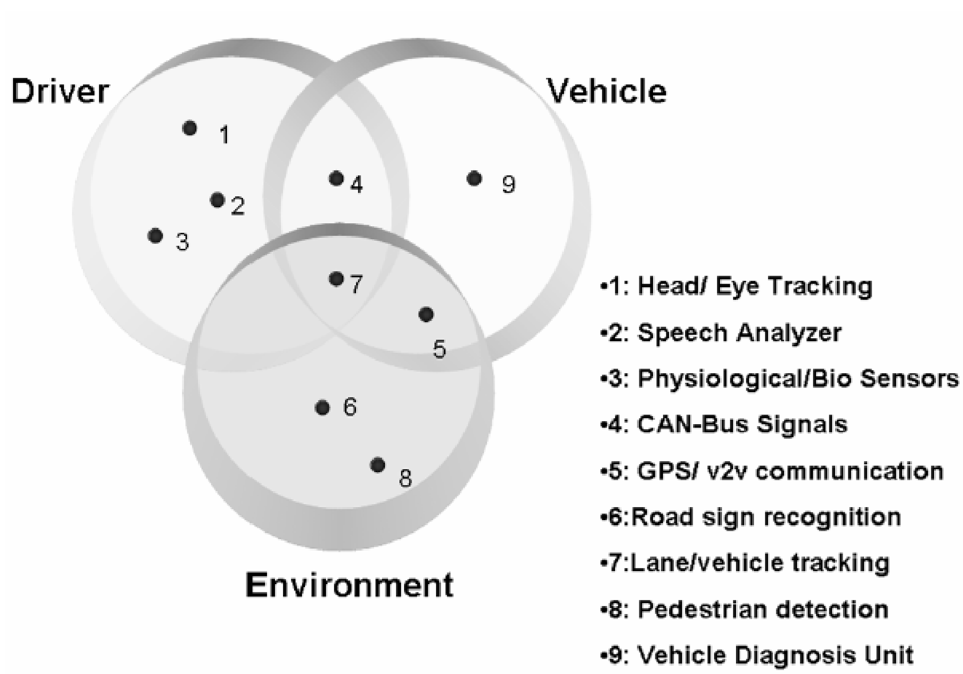



**Figure 2** Mapping of sensors in AVS systems to three main domains of driving dynamics



One of the most convenient approaches is to identify the context, and then assess if there is any deviation from the expected 'normal' manoeuvre/behaviour. Therefore, the system mainly consists of two sub-modules:

1 the first sub-module identifies the instant context of driving in terms of expected manoeuvres or regulatory tasks

2 the second sub-module quantifies any deviations from the baseline for that particular context and outputs the measure together with a trigger to be delivered to correspondent actuators or a supervisory controller system.

These sub-systems require three different pattern recognition problems to be solved in real-time:

1 *Context recognition*: this involves classification of manoeuvres and regulatory tasks which can be used to reconstruct any route and context of driving. For this investigation, the manoeuvres are considered to include right turn (RT), left turn (LT), lane change (LC) and stop (ST). For straight segments of the road where no manoeuvres are required, the task can be classified either as lane keeping for straight segments (LKS) or curved segments (LKC). LKS and LKC are considered as regulatory tasks during driving which are essentially different from other manoeuvres which include perception, cognition, decision or action sequence. From a pattern recognition point of view, this problem can be considered as a 7-class classification problem. Therefore, it requires an optimum set of features which would separate these classes with the highest of accuracy. Another issue with selection of optimal features is that the calculations should not be costly in terms of time.

2 *Abnormality detection*: this relates to detection of deviations from the 'normal' signals for each manoeuvre or regulatory task such as lane keeping (LKS) or curve negotiation in LKC. Deviation from the normative behaviour may be caused by distraction, sleepiness/drowsiness or stress. Even ignoring the cause of the deviation, a module based on CAN-Bus can reveal at least the abnormalities. Essentially, this solution can be considered a two class problem for distinguishing abnormalities from normal signals.

3 *Prediction of distraction level*: this requires expanding the solution to Problem 2. To quantify the levels, results from human factors will be employed to map several tasks to their predicted distraction levels and used in supervised training.

To obtain viable solutions to these three problems, the methodology will follow these steps:

1 explore generic feature definitions for recognition of a manoeuvre

2 define manoeuvre specific features/driver performance metrics to distinguish abnormalities/deviations

3 use feature selection methodologies to obtain a compact reliable feature set for three 'pattern recognition in time series' problems described above

4 implement manoeuvre recognition (context recognition) and abnormality detection sub-modules with selected feature sets and evaluate their performance.

Before moving into details of the methodology here, it is necessary to mention the dimensions of the problem at hand since it helps construct a road-map for achieving an effective AVS system. A categorisation of applications is given in Figure 3 leading to different AVS structures. For both context recognition and abnormality detection, the application can be either

1 generic

2 person-specific.

Generic systems are expected to address 95% of drivers with reasonable reliability, with acceptable false alarm rates (i.e. <2%). Designing such a generic system is difficult because of the highly dynamic nature of the driving task including the variations between drivers, conditions and even discrepancies between driving sessions on the same route by the same driver. Previous work has concentrated on designing a generic system for context recognition and abnormality detection using stochastic methods with non-optimal features (Boyraz et al., 2007; Sathyanarayana et al., 2008). An alternate to generic approach, person-dependent systems reduce the effect of inter-driver variation on the performance of recognition. However, driver-dependent AVS systems require the personal driving characteristics and/or biometrics to be stored on the in-vehicle system. Driver-dependent AVS is expected to have at least three sub-modules

1 *Driver identification*: expected to use speaker and/or face recognition or a smart key to reduce the complexity of driver monitoring.

2 *Manoeuvre/context recognition*: expected to monitor and recognise the context of the driving to reduce the complexity of abnormality detection task.

3 *Abnormality detection*: given the specific driver characteristics/models and context, this model is expected to detect abnormalities (i.e. due to distraction, sleepiness, inattention).

A preliminary driver-dependent framework has been designed and evaluated in previous work (Boyraz et al., 2008).

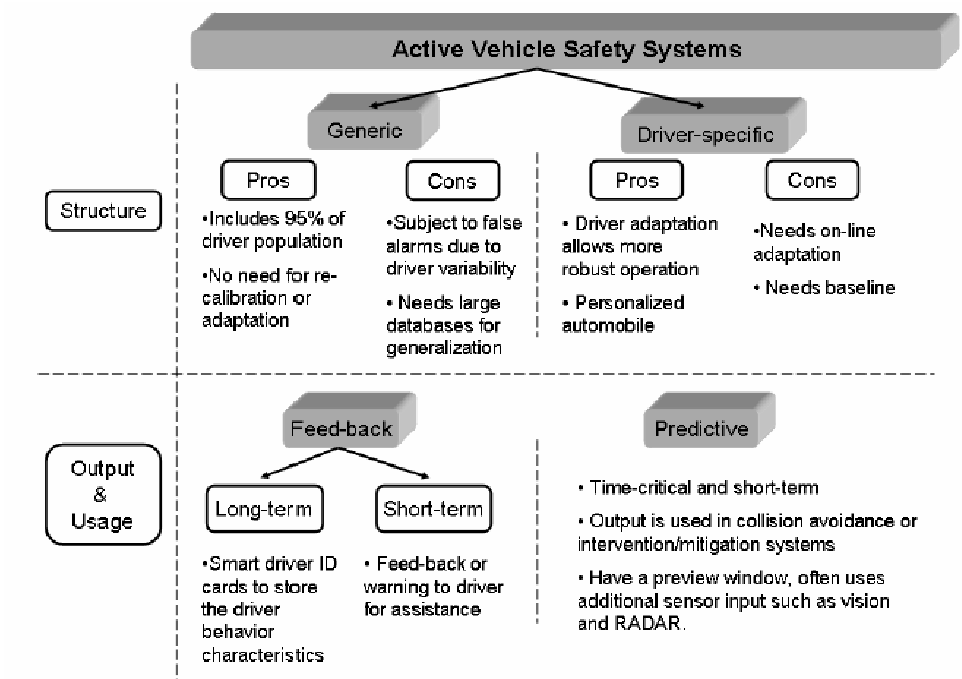
Another categorisation of AVS systems is related to functioning or operation mode. According to how the system is expected to operate, it can be:

1 predictive/feed-forward

2 feed-back.

Predictive systems are expected to measure and analyse the immediate future path of the system in a state-space manner and act upon the result, and hence are extremely time-critical. A predictive system can be employed both as a warning/driver assistance system and a supervisory system to activate the controllers and intervene in driving if an immediate accident is perceived by peripheral sensors such as radars and vision systems. Feed-back systems need not be predictive and are therefore less time-critical. These systems should assist the driver, providing feedback as warnings on their performance. From an AVS system design perspective, the feed-back systems are neither completely active nor passive safety devices, but they do aim to improve driver behaviour and are not designed to intervene and take control of the vehicle.

**Figure 3** AVS systems categorised according to their data/structure and output/end-use




The proposed system in this paper will be a generic-type in terms of design, and feedback-type in terms of operation-mode. However, upgrading the system into a predictive one is not difficult if CAN-Bus information is used along with the corresponding computer vision and radar systems providing predictive information on the road ahead. In addition to this, time-critical recognition will be separately evaluated as a first step towards predictive AVS. Two main research phases are considered here.

First, context recognition achieved using driver–vehicle interaction signals from CAN-Bus can be named the ‘manoeuvre recognition module’. If GPS and road scene video are available, then the manoeuvre recognition is only used as a redundant module to confirm what is inferred from the former two. However, when these two information sensors are not available, CAN-Bus-based manoeuvre recognition can provide reliable context information, at least at the manoeuvre level for the abnormality detection. For manoeuvre recognition system this involves classifying the upstream signals into the eight previously defined clusters, representing the most encountered manoeuvres. To design such a system, the crucial question is ‘What is the optimal feature set for CAN-Bus time series to distinguish between different manoeuvres?’ Therefore, the main aim for this part is to define a discriminative feature set to obtain classification results with clusters as separable from each other as possible. To obtain a preliminary feature set to be optimised, we employ two different approaches:

1 Canonical signal reduction methods in the time series, particularly Fourier Transform and wavelet decomposition (WD).

2 Statistical feature definition using histogram-based calculations over a time window in a time series.

For classification algorithms, we follow two separate approaches in line with these feature sets:

1 ANN

2 SVM to work with feature vectors.

The results are used to determine the most effective compact feature set, independent of the classification algorithm. Therefore, to optimise the feature set, we employ unsupervised clustering as a guideline. To assess the predictive capability of our manoeuvre recognition system, partially incomplete signals are used as a separate test batch.

Second, for abnormality detection, each manoeuvre is investigated separately using:

1 physical cues of vehicle dynamics

2 human factors research to define the nominal manoeuvres

3 pre-labelled normal manoeuvre of that class.

Based on these nominal definitions, the best set of features to measure deviations/abnormalities is sought after for each manoeuvre. Abnormality detection can be viewed as a 2-class classification problem or a multi-class level-of-abnormality problem. Both of these are considered in the investigation to lay the foundation for predictive AVS, since the output of abnormality detection can be used by controllers to avoid accidents.

## 3 Data collection and organisation

In this section, the data collection vehicle, experimental procedure and corpus organisation are presented. Firstly, the instrumented vehicle is introduced briefly together with sensors. Secondly, the data collection procedure and corpus organisation is with a description of the corpus demographics. Finally, a much needed tool in multi-media signals processing/driver data analysis is introduced for data annotation section. In addition to the synchronised data annotation tool (UTDAT), a colour-code representation for the driving time-line is proposed as a standardised visualisation tool for interpreting and analysing extensive volumes of driving data, increasing the efficiency of exploratory research in this area.

### *3.1 Instrumented vehicle: UTDrive multi-sensor research platform*

The data collection vehicle is a Toyota RAV4 equipped with following sensors as illustrated in Figure 4:

- two CCD cameras for monitoring the driver and the road scene (resolution 480 × 640 pixels, 30 frames/sec)
- custom-designed microphone array (5 microphones) to capture driver's speech as well as environment noise conditions in the vehicle

- a close talk microphone to obtain driver's speech with reduced noise content
- optical distance sensor to obtain the headway distance between the equipped vehicle and other vehicles in traffic
- GPS for location tracking
- CAN-Bus OBD II port for collecting vehicle dynamics: vehicle speed, SWA, gas and brake inputs from driver
- Gas/brake pedal pressure sensors to collect information concerning pressure patterns in car-following and braking behaviour.

All data collected from these channels are synchronised and time stamped during the acquisition stage using a multi-channel data acquisition unit DEWETRON (2009) Synchronised data collection facilitates both data mining and multi-sensor information fusion in later stages. The data acquisition interface can be seen in Figure 5, depicting audio signals along the top row, video channels; road (left) and driver (right) scene, CAN-Bus signals and GPS at right bottom corner.

**Figure 4** Instrumented data collection vehicle: UTDrive multi-sensor research platform

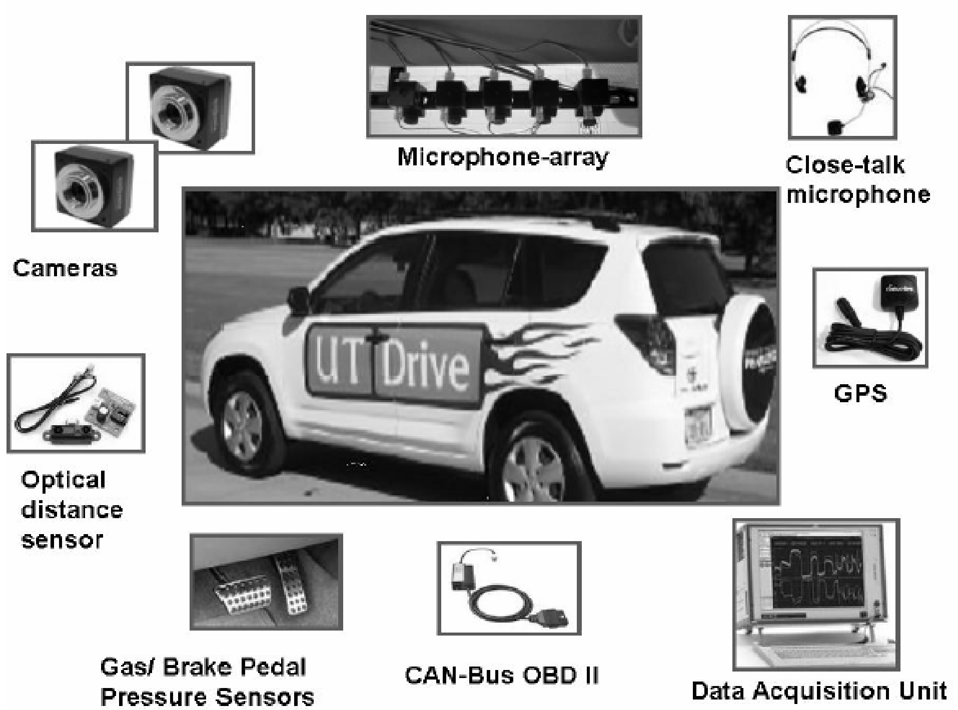


**Figure 5** Data acquisition interface showing audio signals, video channels, CAN-Bus and GPS

## *3.2 Database: UTDrive Corpus*

UTDrive Corpus includes data from previously noted sensor channels (13 separate data streams: 2 video, 6 audio, 1 GPS, 1 optical distance, 1 CAN-Bus, 2 pressure sensors located on the gas/brake pedals). The corpus contains a balance in gender (37 male, 40 female), age (18–65) and different experience levels (novice to expert) in driving. To examine the effect of distraction and secondary common tasks (CT) on these driver groups, a close-to naturalistic data collection protocol is used. The routes taken during data collection are given in Figure 6, and comprise of a mixture of artillery, service and main roads in residential (left) and business districts (right) in Richardson, TX. Each driver participating in the study is required to drive these two routes at least twice in each session to obtain a baseline and a distracted version of the same route. A session includes a mixture of several secondary tasks as listed in Table 1 taking place in the road segments depicted in Figure 6. According to this protocol, a participant gives 12 runs of data with 6 being baselines for that day and that route, the other half featuring several distraction conditions. Each session is separated by at least 2 weeks in order to prevent driver complacency with the route and vehicle. Almost 60% of the data in the corpus consists of a full session profile from drivers; the remaining part contains incomplete sessions and data portions due to of consent of the participant not to continue data collection or one of potential 13 sensors failures. The secondary tasks represent a low to mild level of cognitive and mental load for the drivers. A suggested break-down of tasks and the perception channels they load in the driver's driving process is shown in Figure 7. It should be noted that the distribution is just a guideline to depict the workload involved in each task, and LCs included here are not voluntary but prompted; therefore seen as a task and not a driver event. Regarding the question as to what degree each task loads these perception channels, and what would be the impact on total driving performance we proposed four different hypotheses which are detailed in the next section as part of presenting data annotation tool. The distraction tasks consists of in-vehicle navigator directed lane-change, road sign reading (SR), conversation with the in-vehicle operator and the dialogue interaction using cell-phone. The two dialogue systems were Tell-Me (TM) (voice portal for general info and news) and American airlines (AA) (real-time interaction for flight arrival and departure info from Dallas-Fort Worth airport (DFW).

**Figure 6** Data collection routes: residential (left), business (right) segmented to show assigned tasks

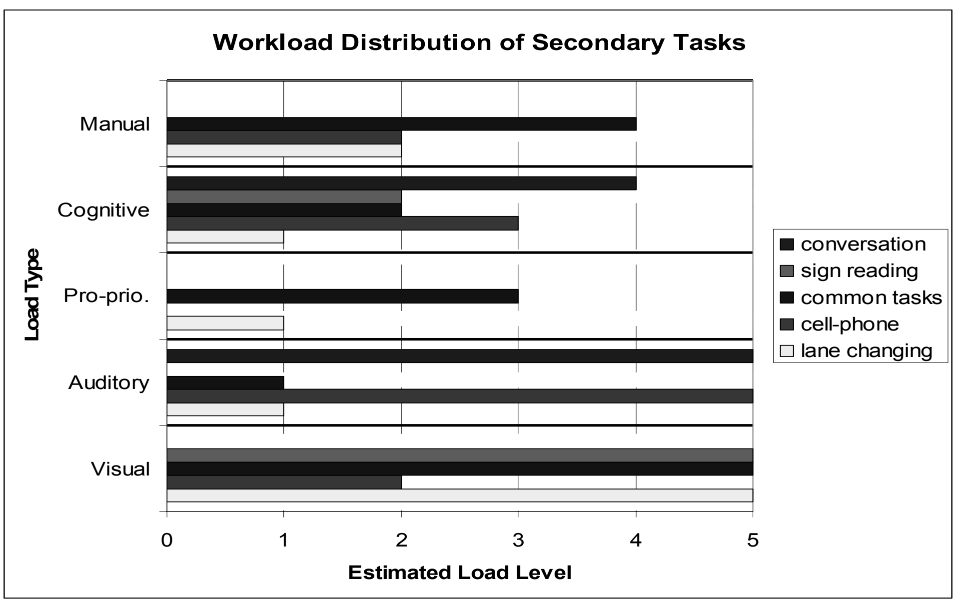

**Table 1** UTDrive corpus data collection protocol

| | | *Secondary tasks* | | |
|---|---|---|---|---|
| | *Part* | *A* | *B* | *C* |
| Route 1 | 1 | Lane changing | Common tasks (radio, *AC*, etc.) | Sign reading |
| | 2 | Cell phone dialogue | Cell phone dialogue | Conversation |
| | 3 | Common tasks | Sign reading | Spontaneous |
| | 4 | Conversation | Spontaneous | Cell phone dialogue |
| Route 2 | 1 | Sign reading | Lane changing | Common tasks (radio, *AC*, etc.) |
| | 2 | Cell phone dialogue | Cell phone dialogue | Conversation |
| | 3 | Common tasks (radio, *AC*, etc.) | Sign reading | Lane changing |
| | 4 | Spontaneous | Conversation | Sign reading |

**Table 1** UTDrive corpus data collection protocol (continued)

| Part | *Secondary tasks* | | |
|---|---|---|---|
| | *A* | *B* | *C* |
| | *Session 1* | | |
| Route 1 | | Just drive | |
| Route 1 | | Secondary task A | |
| Route 2 | | Secondary task A | |
| Route 2 | | Just drive | |
| | *Session 2* | | |
| Route 1 | | Secondary task B | |
| Route 1 | | Just drive | |
| Route 2 | | Just drive | |
| Route 2 | | Secondary task B | |
| | *Session 3* | | |
| Route 2 | | Secondary task C | |
| Route 1 | | Secondary task C | |
| Route 2 | | Just drive | |
| Route 1 | | Just drive | |

**Figure 7** Workload distribution of secondary tasks to visual, auditory, proprioreceptive, cognitive and manual loads



### 3.3 Data annotation tool: UTDAT and colour-coding for driving timeline (CCDT)

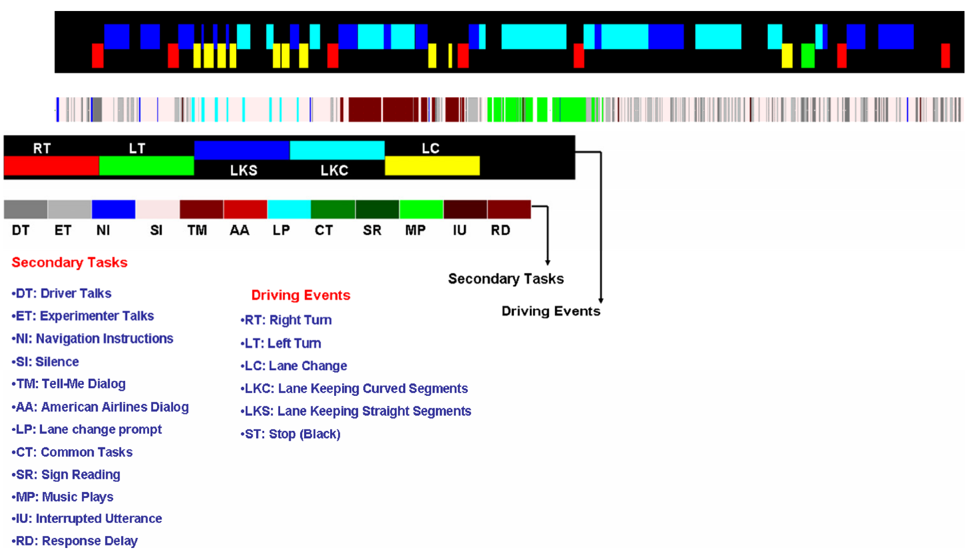
Data annotation is the most crucial step in analysis of any multi-sensor data set since it provides the basis for further signal processing. It should be noted that although segments of the roads are assigned to different tasks, and driving events can also be detected using this information, the data collection is highly dynamic in nature since it takes place in real-traffic. Therefore, it is required to tag the events and tasks to record their time tags (begin–end). For this particular study, the interest is to recognise the driving manoeuvres and detect distractions; therefore two different transcription files are prepared for each run. First, using video streams and CAN-Bus channels, driving events are tagged having six different labels: RT, LT, LC, LKS, LKC and ST. The events constitute the driving event time line parsing the session into meaningful parts which need to be examined separately. The second transcription process involves time-tagging of 12 important task-related events using the audio signal together with video. These 12 labels are: driver talks (DT), experimenter talks (ET), navigation instruction (NI), silence (SI), TM dialogue system, AA dialogue system, lane change prompts (LP), CT, SR, music playing (MP) and two additional driver-response related tags; interrupted utterance (IU) and response delay (RD). The UTDAT data annotation tool is written using MATLAB GUI and shown in Figure 8. This tool consists of four windows (from top left) audio, video, CAN-Bus (lower-left) and transcription (lower right) panels.

To facilitate the analysis of large-size multi-sensor driving data, a colour code for the driving timeline is prepared, visually marking the aforementioned events and task labels with certain colours and projecting them as two parallel time-lines. An example of the timeline is shown in Figure 9, with the legend of the colour coding for driving timeline (CCDT).

The representation in Figure 9 can be used as a coded way of representing the driving history of the driver (driving characteristic print, almost looking like a DNA sequence) without pertaining privacy issues. There might be other venues of exploiting this coding protocol; such as storing driver's favourite routes and driver characteristics in a succinct way; however, we will strictly use it here as a signal history reference for our analysis. Using CCDT, it is possible to observe the events and secondary tasks in a session simultaneously. This visualisation tool is heavily used in further analysis stages for building the distraction/work-load hypotheses, which exploits the overlaps between task and events in the timeline for a multi-layer data analysis.

**Figure 8** UTDAT multi-media data annotation tool, capable of cross-referencing and synchronisation of 2 video, 1 audio and CAN-Bus streams


**Figure 9** Time line of driving events (black band) and tasks (white band) depicted in CCDT (see online version for colours)



## 4 System implementation and results

In this section, a subset of the UTDrive Corpus is employed using all available sessions from 10 female and 10 male participants to design the signal processing modules the depend only on CAN-Bus information (60 sessions of multi-sensor data). The first system involves manoeuvre recognition and is particularly needed for active safety applications since the driving context is important in assessing if the driver is at risk of having an accident or not. The second system is a distraction detection module using manoeuvre/context information together with signal energy/complexity properties and vehicle dynamic norms.

### *4.1 Manoeuvre recognition*

A general signal decomposition approach is employed using fast Fourier transform (FFT) and WD. The coefficients and different level of analysis results from these decompositions are taken as features to represent the CAN-Bus signals, reducing the dimension of the time-series. After obtaining the feature space, a cluster analysis is performed to observe the distribution of the features. Next, geometric constrains for clustering are examined and support vector machines (SVM) are determined to be convenient for manoeuvre classification task via supervised clustering. As a final step to explore potential real-time applicability of the system, a time-window duration analysis is also performed.

#### *4.1.1 Background on FFT and WD for time-series analysis*

Fourier transform has been one of the main tools in time series analysis, especially in the examination of spectral attributes of data. In this framework, the FFT is used for data reduction. Most coefficients of the FFT have small values and even if they are ignored the original signal can be approximated reasonably well; however, this is equivalent to having the signal filtered by a low-pass filter. This property makes the FFT a perfect match for manoeuvre recognition using driver–vehicle interaction signals. However, although Fourier transform is well suited for frequency domain analysis, it loses time-location information. A discrete Fourier transform (DFT) can be calculated as seen in Equation (1) having the time series represented by $T = \{x0, \ldots, xN-1\}$.

$$\mathrm{DFT}(T) = x_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k(n/N)} \quad (k = 0, \ldots, N-1) \tag{1}$$

FT and WD are both orthogonal function families; however, WD uses scaling and shifting therefore having localisation property and multi-resolution. In addition to this, FT is usually more appropriate for smooth functions whereas WD can approximate local discontinuities and jumps well. WD coefficients can also be interpreted as low and high frequency content. The approximation provided by mother wavelet can be considered as low frequency content/general signal trend whereas the details provided by father wavelets constitute high-frequency content in the signal. Haar wavelet function family which is used in this paper in the next sections is given in Equation (2).

$$\psi(x) = \chi_{[0,1/2)}(x) - \chi_{(1/2,1)}(x)$$

and

$$\psi_{j,k}(x) = 2^{j/2}\psi\left(2^j x - k\right) \quad j, k \in Z \tag{2}$$

In the next sections, the resultant feature space distributions are given after FFT and WD applications. The effect of the time window is discussed separately.

## *4.1.2 FFT analysis*

Three important channels (SWA, speed and brake) from CAN-Bus are used in FFT analysis to compress their content to be used in cluster analysis. First, the full length of the signals is used to calculate the FFT and only the first coefficient is taken to represent the single channel information. This led to formation of 3-D feature space that is shown as a 3-D scatter in Figure 10.

From the scatter plot in Figure 10, it is clear that the clusters constituting different manoeuvres are easily distinguishable. A clustering result using simple geometric constraints (2 lines and 2 parabolas and a 2-D plane to set the borders between clusters) is given in Table 2. The clustering performance is further improved with the application of SVMs in following sections.

**Figure 10** 3-D feature space formed by first coefficients of FFT using full length signals: SWA, speed and brake

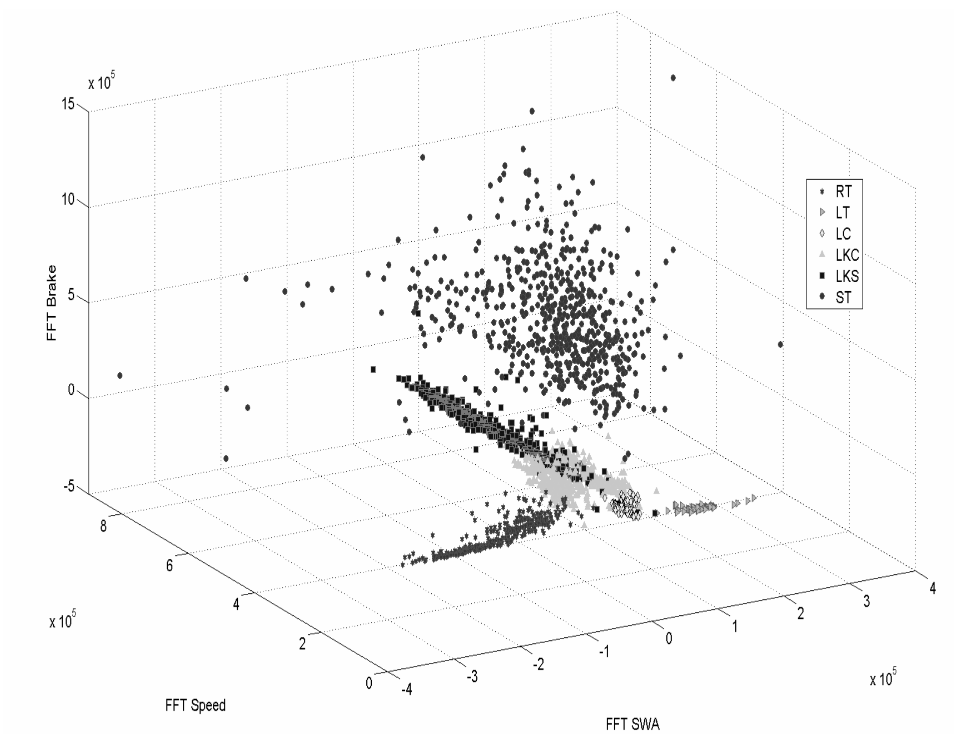


**Table 2** Clustering results on FFT feature space using full length

| | | |
|---|---|---|
| True positive rate | TPR = TP/P | 0.937 |
| False positive rate | FPR = FP/P | 0.008 |
| Accuracy | ACC = (TP + TN)/(P + N) | 0.937 |
| Specifity | SPC = 1 − FPR | 0.991 |
| Positive prediction value | PPV = TP/(TP + FP) | 0.958 |
| Negative prediction value | NPV = TN/(TN + FN) | 0.991 |
| False discovery rate | FDR = FP/(FP + TP) | 0.041 |

Table 2 demonstrates that just using simple geometric decision surfaces between clusters it is possible to classify the manoeuvres (6-class problem) with 93.7% accuracy and a low false positive rate (FPR) (0.8%). These encouraging rates indicate that the system might have potential to be deployed as a basic manoeuvre recogniser when GPS, turn signal and video information is not available. The next important question, if the system can recognise the manoeuvres on their onset with narrower time windows, is explored separately. The next session explores the alternative time-analysis kernel looking at the potential of wavelet functions.

#### *4.1.3 WD analysis*

The same signals used in FFT analysis are used in WD analysis to observe if they can provide better separation. Different wavelet types (i.e. Haar, Daubechies and Symlet) are used in the exploratory phase with several levels of decomposition trials. Haar wavelet has been selected due to its simplicity and 16th level is identified to provide only one coefficient for the signal. The only coefficient provided by Haar WD on 16th level is used for each channel to form a new 3-D feature space which is plotted in Figure 11.

As noted in the comparison of Figures 10 and 11, the wavelet 3-D feature space maps the clusters closer to each other; therefore, we decided to use the potential of wavelet for the abnormality detection and not for manoeuvre recognition. Therefore, the remaining part of the manoeuvre recognition system design will consider only the FFT feature space (Figure 10). It should be noted, however, that since we only search for a single coefficient from each channel, the full potential off the wavelets are not exploited here. The wavelets are employed at lower level decompositions for separation of high and low frequency content for abnormality detection in Section 4.2.

#### *4.1.4 SVM and clustering*

The 2-D projection of the clusters seen in Figure 10, with the exception of the ST class is shown in Figure 12. Since the clusters are located well in the 2-D FFT space as well, we performed an SVM clustering analysis that includes five classes. Since the ST has FFT-Brk dimension drastically different from any other driving event, that we have clustered this manoeuvre simply by using the brake channel.

**Figure 11** 3-D feature space formed by only coefficients given by WD using Haar at 16th level

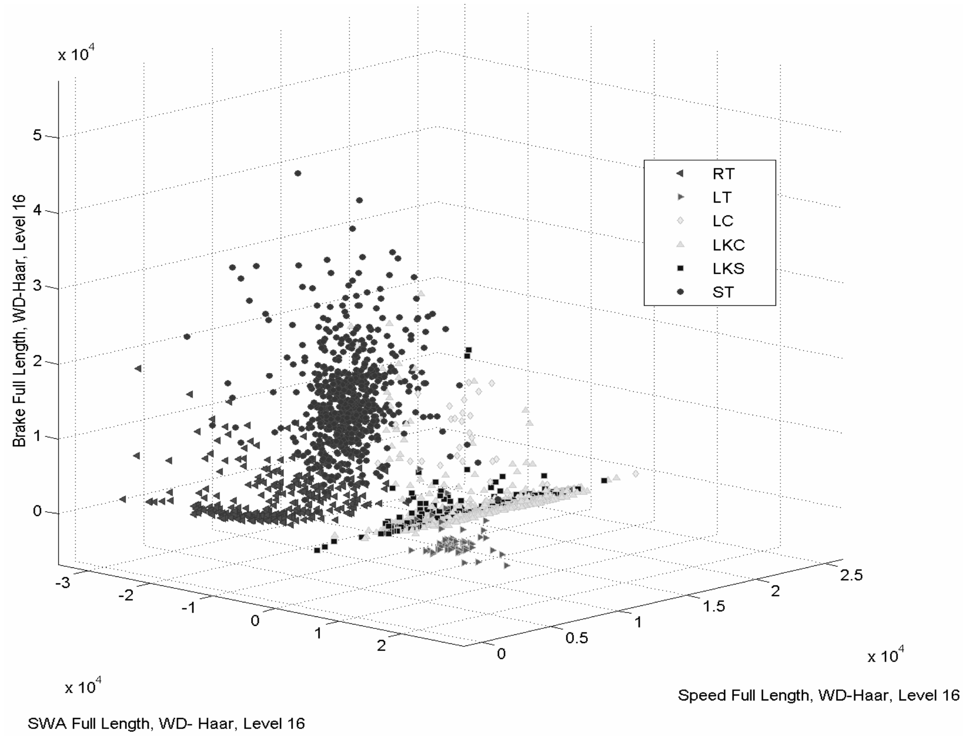
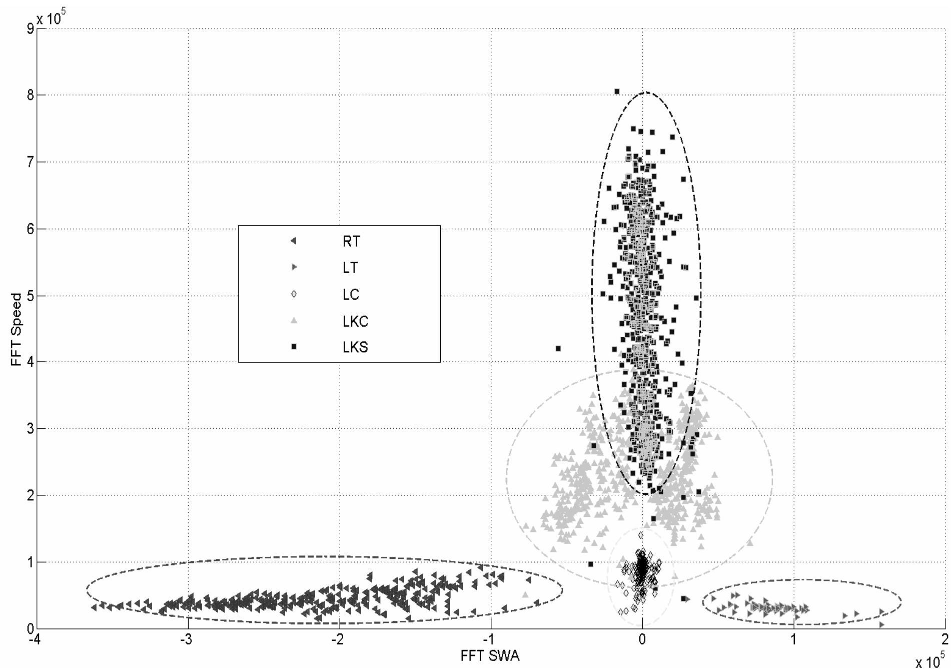



**Figure 12** 2-D feature space formed by FFT from SWA and Brk channels of CAN-Bus



One-against-all algorithm is applied to find the optimum support vectors separating the manoeuvre clusters. Here, 150 manoeuvres for each class are used for training and four different sets of over 100 manoeuvres are used for testing, where each class comprises all 20 drivers' neutral and distracted manoeuvres (LT has a lower number since it does not occur often in the routes). The result of the classification on the test set comprising 463 manoeuvres in total is shown in Figure 13. As expected, results are not significantly different from the geometric constraints applied in the feature space, but a definite improvement in accuracy and false alarm rate is observed. In fact, the accuracy of the SVM classifier is 99%, with the only confusion occurring between the LKS and LKC pair. However, it must be noted that if the algorithm is required to work in real-time, it is better to save the support vectors, or geometric constraints, as classification constraints in a look-up table format for faster operations.

#### *4.1.5 Time-window analysis*

In active safety systems, the prediction capability and accuracy of the system are prior design criteria. However, if the system is required to work in narrow time windows (i.e. the systems to be employed as modules in predictive and intervention systems), these criteria need to be viewed from a time analysis perspective. Therefore, a time-window analysis was performed to measure the accuracy of the generic manoeuvre detection system. As can be seen from Figure 14, when the time analysis window length decreases from 5 to 1 sec, the accuracy drops to 68%. Acceptable accuracy is above 90%, and this rate is reached at a 5 sec analysis time window. Considering that RT, LT and LC might take equal or less time than this time-window; reflect the poor overall system performance as the analysis time decreases. However, the poor accuracy is caused by LKS and LKC manoeuvres, since they require longer time windows to be recognised. Taking this fact into account, a separate plot showing only RT, LT and LC manoeuvres is examined. From Figure 15, it can be seen that at a 1.5 sec time window length, acceptable accuracy is accomplished. Moreover at 3 sec, the FPR drops to 3% which is only 1% away from a deployable system.

### *4.2 Abnormality detection and level of distraction estimation*

In this section, the second module of the AVS system is implemented for detecting abnormalities in driver–vehicle interaction signals from a driver behaviour and performance point of view. This system attempts to expand CAN-Bus-based diagnostics to driver dynamics for an on-board human-centric active safety module. To achieve this, the abnormality and distraction is first defined and our four hypotheses for distraction level with respect to task difficulty and overlap between important driving events and secondary sub-tasks are considered. This part of the study has a two-fold contribution, since it searches for quantitative metrics for distraction detection in addition to testing different hypotheses derived from human factors research through a classification scheme.

**Figure 13** Classification results for 463 test manoeuvres for 5-class using one-against-all SVM algorithm

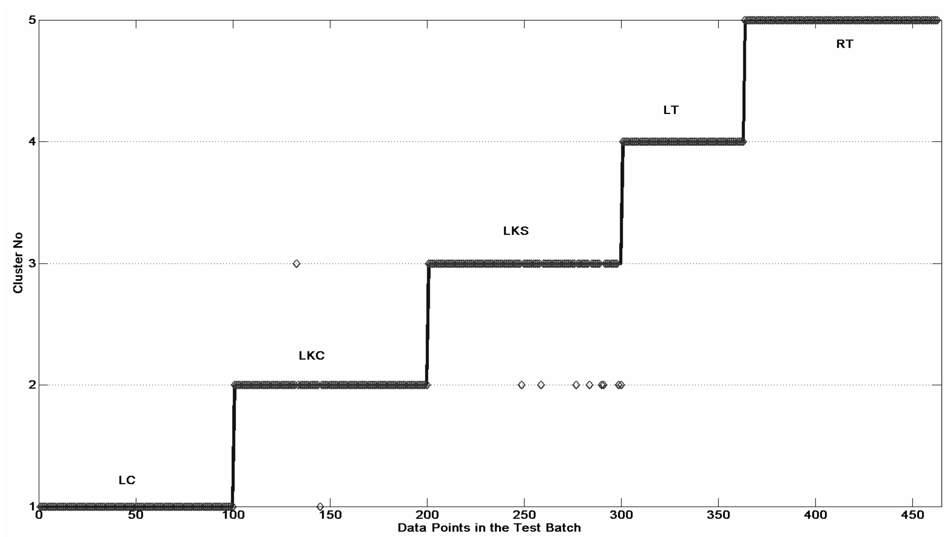



**Figure 14** Accuracy of generic manoeuvre recognition with varying time window lengths

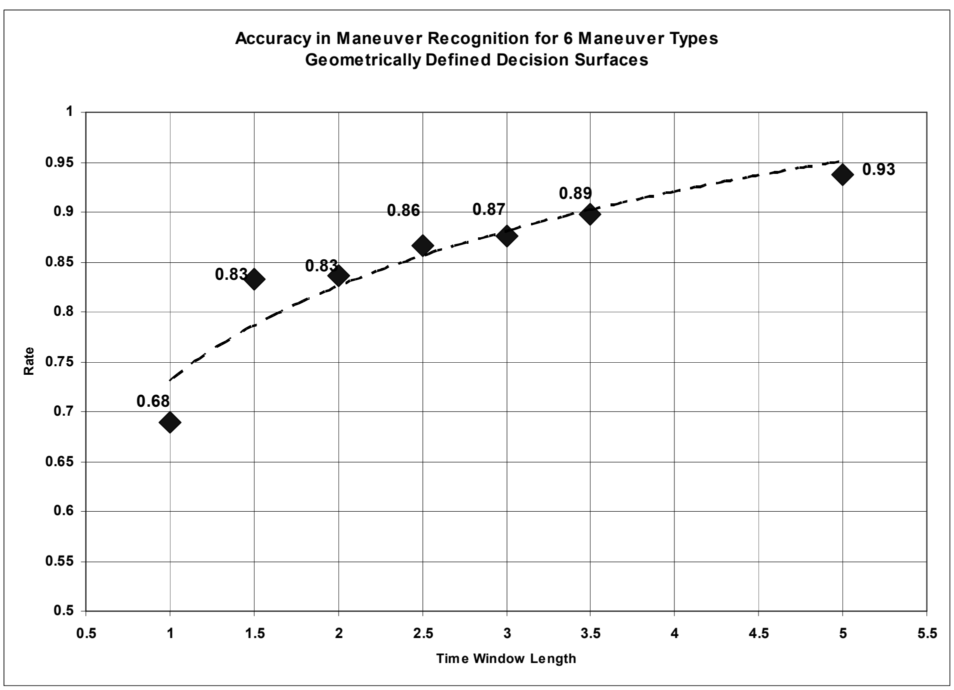
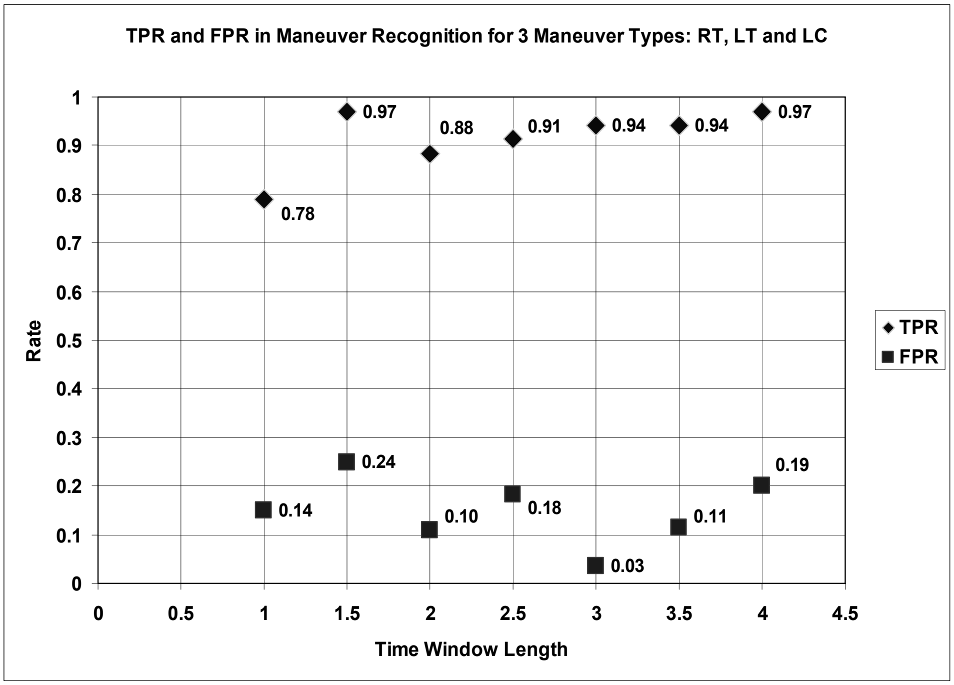


**Figure 15** True positive and FPRs of generic manoeuvre recognition including only short-term manoeuvres (i.e. RT, LT, LC)




## *4.2.1 Definition of abnormality and distraction*

Distraction can be defined as any secondary task, internal condition or external stimuli diverting the attention of the driver. In addition to this, driver performance and attention span can be affected by sleep deprivation, fatigue, intoxication or physiological conditions. This broad spectrum can be grouped under the category of 'abnormality'. Although this paper only focuses on the effect of distraction due to secondary tasks, any of the aforementioned conditions may cause a similar observation in the resulting driver–vehicle interaction signals. It has to be noted that it is not easy to propose quantitative metrics for such an ill-defined and ambiguous daily phenomena; however, a general systematic approach is followed isolate some part of the problem. For example, the very definition of distraction in quantitative terms may depend on the driving event/manoeuvre itself.

Therefore, the metrics or features proposed are expected to be highly manoeuvre-dependent. It is our motivation that a set of reliable quantitative metrics can be defined based on the normality of the manoeuvre with requires separate analysis of the manoeuvres. This approach makes the first module of an AVS system, manoeuvre recognition, a crucial part of the system since distraction detection relies on recognition of the current manoeuvre. Although, manoeuvre-dependent abnormality detection is a viable approach connected to actual vehicle dynamics and the definition of safe driving behaviour, generic features for abnormality detection are also explored. The next section concentrates on the search for generic abnormality detection using WD and sample entropy (SampEnt) by Boer (2001). Next, any manoeuvre dependent abnormality that can be seen via driver–vehicle interaction signals is defined and metrics calculated. The last section tests the metrics proposed via four hypotheses presented here.

Using CCDT employing the transcriptions an estimated level of distraction is proposed following four different hypotheses on how the secondary tasks affect distraction level.

Hypothesis 1: *All secondary tasks during the driving session have the same level of effect on distraction and driver performance. The effect lasts as long as the secondary task is present. Assuming the arbitrary point in distraction level is represented by Dt, the start and finish of the secondary task is represented by ts and tf, in order. The formulation in Equation (3) can be applied to describe the Dt based on the CCDT*:

$$\textit{If}\ (ts<t<tf),\ \textit{then}\ Dt=1;\ \textit{else}\ Dt=0 \tag{3}$$

*Essentially, this hypothesis is a binary decision based on the distraction being present or not (e.g. on/off).*

Hypothesis 2: *The distraction level is affected by time on task. In other words, the level of distraction is related to the persistency of the secondary task. This is formulated using Equation (4), with additional time tags, es and ef, which represent the start and finish of the driving event.*

$$\textit{If}\ (ts<t<tf),\ \textit{then}\ Dt=(|tf-ts|\ \cap\ |ef-es|)\ /\ (|ef-es|);\textit{else}\ Dt=0 \tag{4}$$

Hypothesis 3*: The distraction level is affected by the task difficulty, and the level remains the same as long as the secondary task is present. The formulation is given in Equation (5).*

$$\textit{For task}\ j,\ \textit{If}\ (ts<t<tf),\ \textit{then}\ Dt=\alpha j;\ \textit{else}\ Dt=0.\ \alpha j \in [1-5] \tag{5}$$

Hypothesis 4*: The distraction level is affected by task difficulty as well as time-on-task overlap between the driving event and the secondary task as expressed in Equation (6).*

$$\textit{if}\ (ts<t<tf),\ \textit{then}\ Dt = aj(|tf-ts|\cap|ef-es|)\ /\ (|ef-es|);\ \textit{else}\ Dt=0 \tag{6}$$

A continuous level of estimated distraction level is calculated based on the CCDT of the driving session. An example showing CCDT, CAN-Bus signals and estimated distraction level according to Hypothesis 4 is shown in Figure 16. For all 20 subjects' sessions in the sub-set database, a similar plot is drawn and saved to help in the exploratory analysis phase.

### *4.2.2 Generic features for abnormality detection*

This section concentrates on two different methods in finding generic features for abnormality detection:

1 WD detailing signals with high frequency coefficients

2 SampEnt.

The first method, WD, separates the signal into approximation and detail parts at different levels. For example, decomposition is seen in Figure 17 for a RT manoeuvre

SWA signal. We propose that the detail signals can capture the fluctuation or high frequency content in the signal; therefore the total energy of the detail signal can form a new metric for micro-corrections in the signal. In fact, micro-corrections in SWA are well-known indicators for distraction or drowsiness (Wierwille et al., 1994). Although initially suggested for lane keeping performance measurement, we will expand the applications of metrics based on SWA high frequency content.

More traditionally, for SWA, SampEnt, standard deviation (STD) and SWA rate (SWAR) are suggested as a means to measure the fluctuations over a time window for driver performance measurement, especially during a lane keeping task (Gunay, 2008). However, SWA can assume extreme levels during RT and LT manoeuvres; this may render statistical metrics unreliable. In addition to that, using metrics for abnormality detection, a baseline for each manoeuvre type is required; otherwise the metrics are not useful since the magnitude of the signals may change due to the manoeuvre itself, but not based on disturbance or distraction. Therefore, metric reliability and hypotheses are assessed using correlation analysis over the entire database. Hypotheses 2–4 explained in Section 4.2.1 are tested using a correlation analysis between generic metrics of energy of WD detail signal (DB4, level 6) and SampEnt for SWA and speed channels from the CAN-Bus. Each hypothesis is considered in two parts; one assuming that all metrics increase and the other assuming that all metrics decrease with the distraction level. After correlation analysis is performed, only correlated cases with $r > 0.1$ and $p < 0.05$ are taken into account. The percent of data complying with these conditions are stated in Table 3. As seen in this table, none of the hypotheses is strong enough to eliminate the others and there is significant amount of data supporting all of them. The time window for calculation of the metrics used in the correlation analysis was 1 sec.

**Figure 16** Estimated distraction level calculated using CCDT shown together with CAN-Bus signals for participant dm4 (see online version for colours)

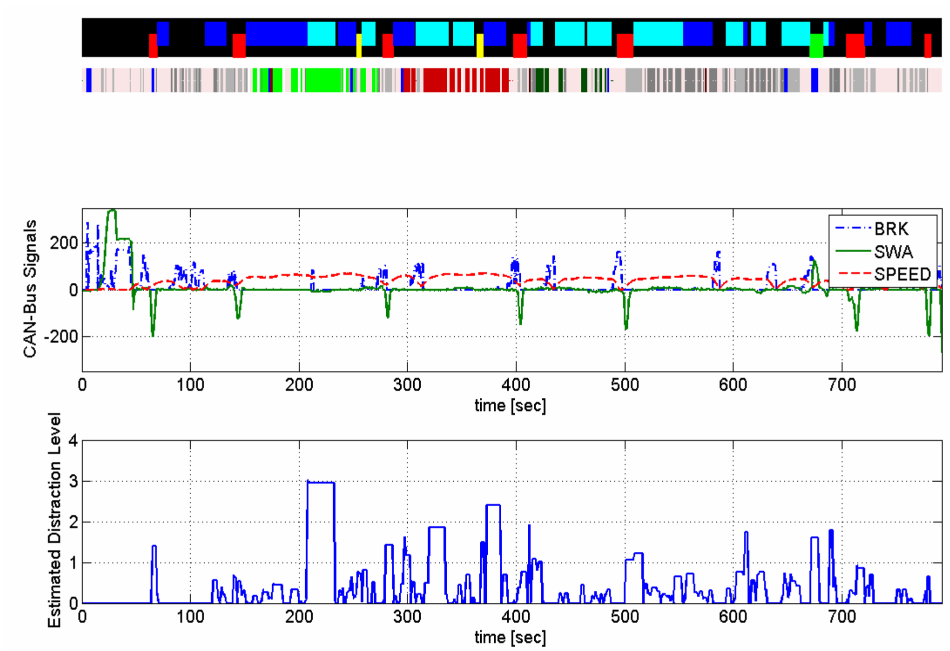


**Figure 17** WD of a SWA signal for RT manoeuvre showing the decomposition tree, approximation and detail signals

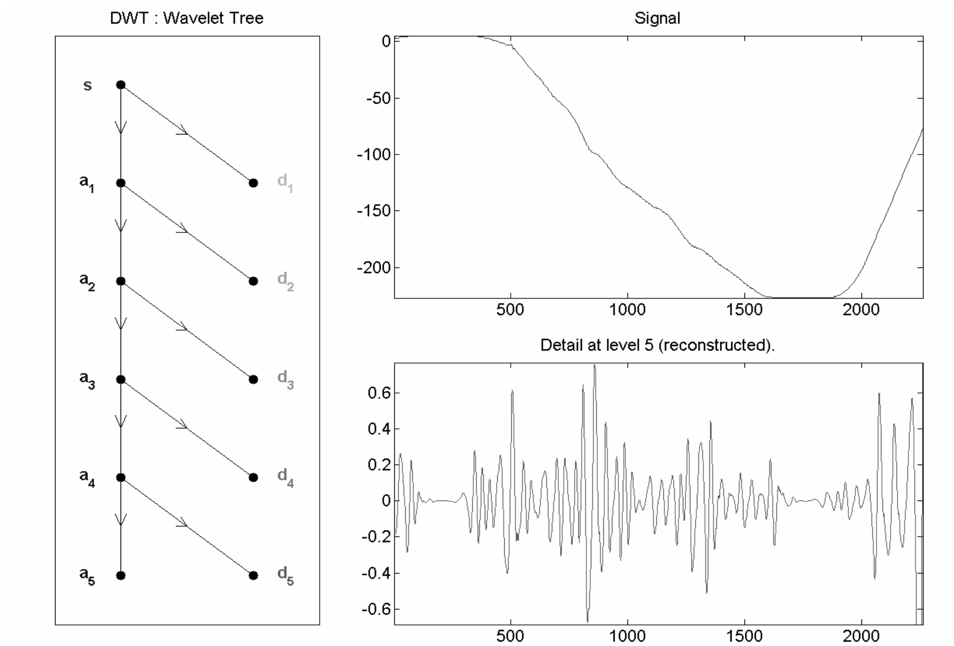



**Table 3** Percent of data complying with Hypotheses 2–4

| *Hypothesis testing* | | *Correlation (r > 0.1, p < 0.05)%* | | |
|---|---|---|---|---|
| *Manoeuvre* | *(+) or (−)* | *Percentage* | *Task* | *Combine* |
| LC | Positive | 54.16 | 58.33 | 54.16 |
| | Negative | 58.33 | 50 | 54.16 |
| LKC | Positive | 25 | 22 | 19.4 |
| | Negative | 38 | 38 | 41.6 |
| LKS | Positive | 17 | 17 | 0 |
| | Negative | 50 | 50 | 0 |
| LT | Positive | 46.8 | 31.2 | 40.6 |
| | Negative | 59 | 62.5 | 53.1 |
| RT | Positive | 50 | 37.5 | 50 |
| | Negative | 37.5 | 45.8 | 37.5 |
| Average + | | 38.592 | 33.206 | 32.832 |
| Average − | | 48.566 | 49.26 | 37.272 |

Table 3 shows that a general trend concerning the distraction detection with proposed metrics and hypothesis cannot be confirmed if all the metrics are expected to increase or decrease together without regard to type of manoeuvre. Therefore, another table is obtained to consider the performance of metrics complying with the hypothesis in terms of percent. Table 4 shows these percentages of metrics correlated with our three hypotheses.

From Table 4, it can be noticed that for a specific manoeuvre metrics might change in different direction from the general positive or negative expectation. Therefore, using this observation a general trend of each metric change for each manoeuvre is constructed as seen in Table 5. In this table, a zero means that hypothesis is wrong and 1 means a true value. Therefore, for example, for LC manoeuvre the pattern of metrics change is (−, +, −, +) whereas it is the reverse for LT and RT.

A new correlation analysis is performed considering the new hypothesis constructed on observations based on metric trends. The results are shown in Table 6.

**Table 4** Percentage of data where the metrics were correlated with the hypotheses

| *Metric testing* | | *Correlation ($r > 0.1$, $p < 0.05$)%* | | | |
|---|---|---|---|---|---|
| | *(+) or (−)* | *SWA_WDE* | *Speed_WDE* | *SWA_Ent* | *Speed_Ent* |
| LC | Positive | 16.6 | 72.2 | 33.3 | 100 |
| | Negative | 88.9 | 38.9 | 72.2 | 16.6 |
| LKC | Positive | 33.3 | 11.1 | 18.5 | 25.9 |
| | Negative | 40.7 | 33.3 | 37 | 48.1 |
| LKS | Positive | 15.4 | 10.2 | 15.4 | 5 |
| | Negative | 28.2 | 46.1 | 23 | 38.4 |
| LT | Positive | 25.6 | 20.5 | 35.9 | 7.7 |
| | Negative | 25.6 | 35.9 | 20.5 | 46.1 |
| RT | Positive | 33.3 | 12.8 | 23 | 15.4 |
| | Negative | 12.8 | 20.5 | 12.8 | 28.2 |
| Average + | | 24.84 | 25.36 | 25.22 | 30.8 |
| Average − | | 39.24 | 34.94 | 33.1 | 35.48 |

**Table 5** New hypothesis and trends in metrics change

| | *New hypothesis* | | | |
|---|---|---|---|---|
| | *SWA_WDE* | *Speed_WDE* | *SWA_Ent* | *Speed_Ent* |
| LC | 0 | 1 | 0 | 1 |
| | 1 | 0 | 1 | 0 |
| LKC | 0 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 |
| LKS | 0 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 |
| LT | 0 | 0 | 1 | 0 |
| | 0 | 1 | 0 | 1 |
| RT | 1 | 0 | 1 | 0 |
| | 0 | 1 | 0 | 1 |

**Table 6** New hypothesis based on metric trends

| *Hypothesis testing* | *Correlation (r > 0.1, p < 0.05)%* | | |
|---|---|---|---|
| | *Percentage* | *Task* | *Combine* |
| LC | 83.3 | 75 | 83.3 |
| LKC | 38 | 38 | 41.6 |
| LKS | 50 | 50 | 0 |
| LT | 71.8 | 65.6 | 65.6 |
| RT | 62.5 | 33.3 | 62.5 |
| Average | 54.9 | 51.8 | 53.6 |

As it can be seen from Table 6, the generic distraction detection with proposed metrics and new hypothesis can be achieved with improved performance (e.g. 83.3% for LC, 62.5% for RT and 71.8% for LT). However, LKS and LKC manoeuvres cannot be assessed with high accuracy in terms of distraction detection with the generic system. The possible causes of the poor performance on LKS and LKC is due to

1 narrow time window (1 sec)

2 driver characteristics and different complacency zones/error accumulation-correction habits of drivers during regulatory tasks such as LKS and LKC.

The next section proposes a manoeuvre and driver dependent, long-term distraction detection system building on these observations from this evaluation.

### *4.2.3 Manoeuvre and driver-dependent system*

CAN-Bus signals can reveal the distraction level of the driver when the variability due to manoeuvres and driver characteristics are eliminated or dealt with so as to not cause false alarms. Therefore, a methodology using abaseline for each individual driver, and particular manoeuvre, is proposed to obtain better detection performance compared to a generic system. A general flow-diagram of the methodology is given in Figure 18. The variation in the signals due to the manoeuvre/particular road segment is eliminated here by manoeuvre classification given in Section 3.1 of this paper.

After the feature extraction process, distraction detection is performed by taking the driver's baseline for a given manoeuvre obtained from the same route segment (marked as 2 in Figure 6) as the neutral conditions. Since the UTDrive Corpus includes multiple sessions collected from the same route and same driver under different conditions, baselines can easily be obtained. The algorithm flow for distraction detection is shown in Figure 19. A normalised comparison ratio ($\alpha$) is calculated for each element in the feature vector. The comparison ratio is used in multiple interval thresholds. Each threshold interval is assigned to a probability. For example, if the ratio is between 0.1 and 1, the probability of distraction is 0.7, and if the ratio is larger than 20, it is 1. Such an assignment approach allows for probabilistic assessment of the distraction, and it can also give an idea of the distraction level.

**Figure 18** Flow diagram of general methodology used for CAN-Bus-based analysis (see online version for colours)

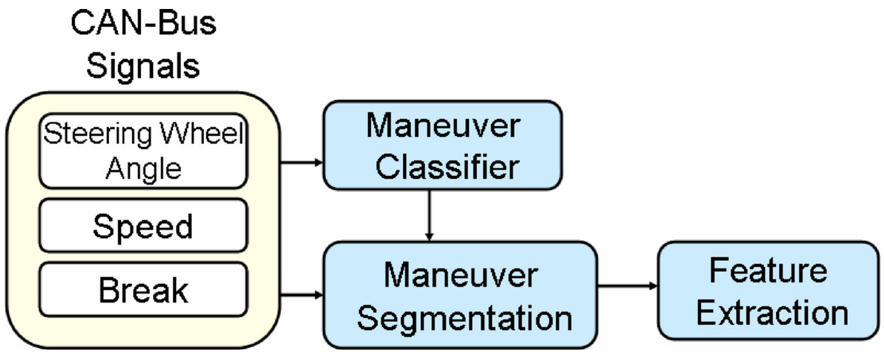
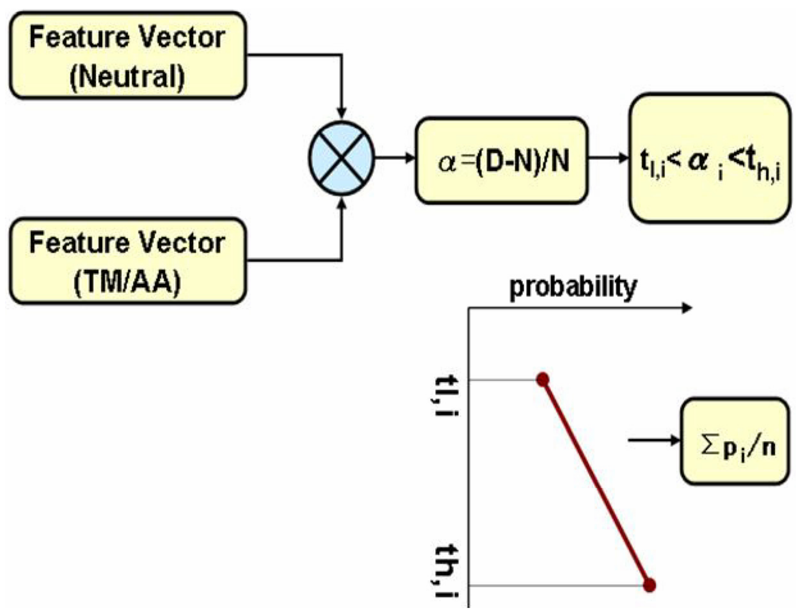



**Figure 19** Distraction detection algorithm flow based on features extracted from CAN-Bus signals (see online version for colours)




Comparison values greater than 0.1 in magnitude are considered as indication of significant distraction. If the comparison value magnitude is below 0.1, the session is assumed to be sufficiently close to baseline to be considered neutral. As the comparison ratio increases, the probability of being distracted increases, with the highest value being 1 as shown in Figure 19. At the end of this probability mapping, the probabilities are summed along the feature vector (now comprising comparison ratios) and normalised by dividing the resultant likelihood value in the feature vector dimension. The next sections explain the feature extraction process and motivation behind the particular feature vector elements selected.

*4.2.3.1 CAN-Bus-based features* The CAN-Bus features are selected based on their relevance to distraction and the definition of the manoeuvre. Using the colour coded driving timeline plots; it was observed that route segment 2 contains lane keeping and curve negotiation tasks in terms of driving. For lane keeping, several driver performance metrics are suggested in the literature, mostly using SWA to calculate a metric indicating the fluctuations or micro-corrections in SWA input. Amongst these metrics, a widely accepted method is the SampEnt (Boer, 2001) and STD. If available, the lane deviation measurements also reflect if the driver is fully attentive and in control. The reversal rate of steering wheel is also considered to be a reliable metric to assess driver performance in a lane keeping task. Boer (2005) recently updated their previous work and suggested adjustments that include taking high frequency terms into account. It was also pointed out in the work by Boyraz et al., a thorough analysis that the speed interval for which the SWA dependent metric is being calculated is important, since lower speeds require more SWA inputs to achieve the same amount of lateral movement of the car compared to a higher speed. For curve negotiation, a constant input angle is required using the visual input of the road curvature. A novice or distracted driver may have fluctuating inputs in the SWA, and their general trend is that the speed should be reduced while taking the curves to balance the centrifugal force. Although different in nature, lane keeping and curve negotiation can be seen as regulatory control tasks from the driver's point of view. Therefore, we selected a seven dimensional feature vector using available information and observations about driver performance/behaviour including: energies of high frequency components WD, SampEnt, STD and standard deviation of rate of change (R-STD). All features are extracted for SWA and speed channels, except for R-STD which is only applied to SWA. The time window length is taken as equal to the manoeuvre length, and the effect of the signal length is eliminated in the calculation of features. The entries of the feature vector are listed with their definitions in Table 7.

For the WD, Daubechies (1988) wavelet kernel with 4th order is used and detail signal is taken at the 6th level. Daubechies wavelet is chosen since it can approximate to signals with spikes and discontinuous attributes well. The level and order are adjusted to be able to extract the high frequency content in the signal which is in the limitation of human control, the higher details are ignored since they might be caused by other disturbances in the measurement rather than driver. Scaling functions (a), wavelet function coefficients (b), scaling function (c) and wavelet function (d) for DB4 are given in Equation group (6).

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}, h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}, h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}, h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}} \tag{6a}$$

$$g_0 = h_3,\ g_1 = -h_2,\ g_2 = h_1,\ g_3 = -h_0 \tag{6b}$$

$$a_i = h_0 s_{2i} + h_1 s_{2i+1} + h_2 s_{2i+2} + h_3 s_{2i+3} \tag{6c}$$

$$c_i = g_0 s_{2i} + g_1 s_{2i+1} + g_2 s_{2i+2} + g_3 s_{2i+3} \tag{6d}$$

SampEnt, which is used as a measure to quantify regularity and complexity of the signal, is a perfect match for measuring the regularity of the SWA signal. It is known that measures based on entropy have long been employed in bio-signal processing such as EEG, ECG and EMG to measure regularity and detect abnormality. The method used here to calculate the SampEnt follows the work described by Xie et al. (2008). The STD is calculated in a canonical form with statistics.

*4.2.3.2 Distraction detection performance* Using the algorithm flow depicted in Figure 19, and feature vectors explained in Table 4, 96 comparison cases for lane keeping and 113 cases for curve negotiation were examined using 14 drivers' (20 sessions, 7 female and 7 male drivers) data. As insight, the WDE_SWA feature member is given for lane keeping manoeuvres in Figure 20. It can be easily seen that the distracted sessions are generally greater than the baseline for this metric. The dashed line represents the mean neutral cases, and solid line represents distraction cases representing the magnitude of the steering wheel angle (WDE-SWA).

**Table 7** Feature vector and definitions

| *Notation* | *Definition* |
|---|---|
| WDE_SWA | WD detail signal energy for SWA |
| WDE_Speed | WD detail signal energy for speed |
| SampEnt_SWA | Sample entropy of SWA |
| SampEnt_Speed | Sample entropy of SWA |
| STD_SWA | Standard deviation of SWA |
| STD_Speed | Standard deviation of SWA |
| STD_SWAR | Standard deviation of SWA rate |

**Figure 20** WD details signal energy for SWA calculated for 96 comparison cases of lane keeping

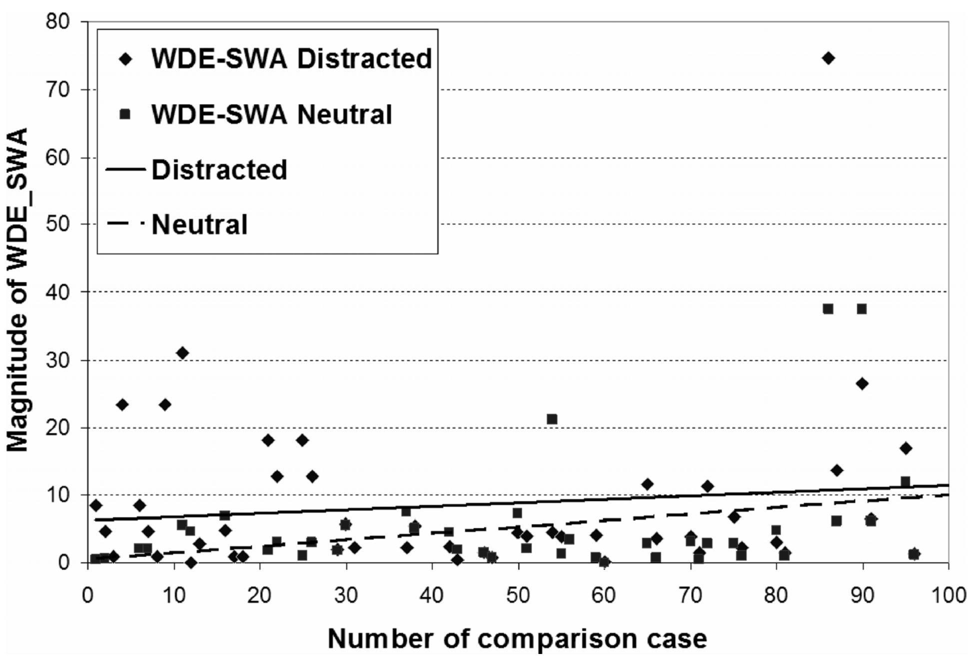


**Table 8** Accuracy of distraction detection

| *Manoeuvre* | *Threshold* | *0.2* | | *0.1* | | *0 (Binary)* | |
|---|---|---|---|---|---|---|---|
| LKS | Count | 72/96 | 62/96 | 84/96 | 76/96 | 95/96 | 76/96 |
| | Accuracy (%) | 75 | 64 | 87 | 79 | *98* | 79 |
| LKC | Count | 65/113 | 64/113 | 82/113 | 79/113 | 95/113 | 79/113 |
| | Accuracy (%) | 57 | 56 | 72 | 69 | *84* | 69 |

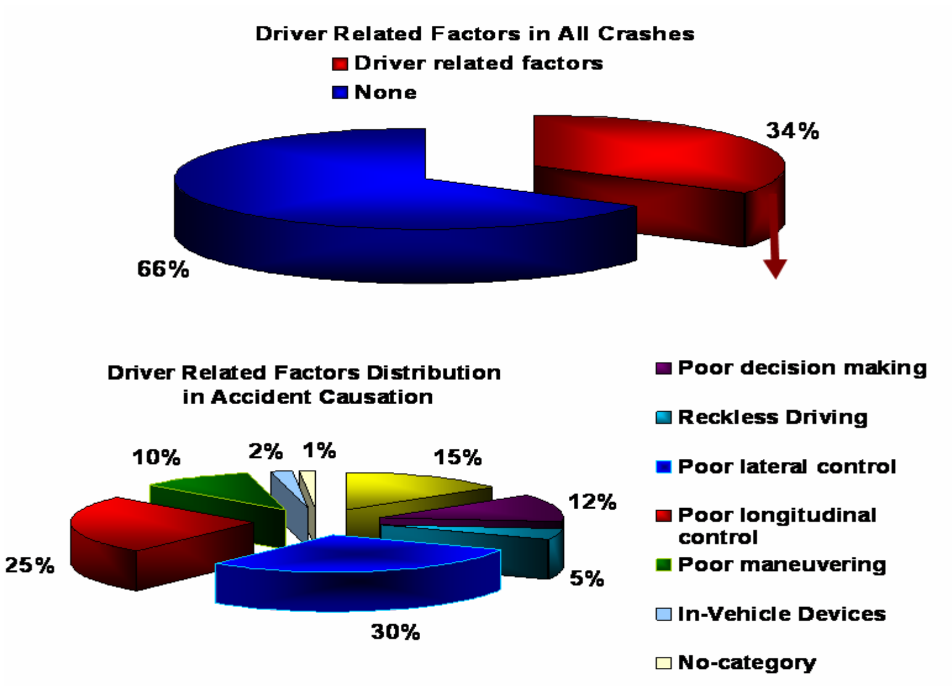
Next, overall performance is considered. The accuracy of distraction detection is given in Table 8 using the seven dimension feature vector (LKS), and using four dimension feature vector subset containing only SWA related features (LKC) with threshold values of 0.2, 0.1 and 0 for the final classification result.

From Table 8, it can be seen that if any probability value higher than zero is taken into account, the distraction can be detected with 98% accuracy using lane keeping segments (LKS), and at an 84% accuracy using curve negotiation segments (LKC) during TM/AA cell-phone dialogues.

## 5 Conclusion and discussions

In this study, driver–vehicle interaction signals available from CAN-Bus was analysed to recognise manoeuvres and detect driver distraction together with its estimated level/impact. This module can be a crucial part in preventative active safety systems to intervene for imminent accidents. In addition to exploring the feasibility of driver-behaviour related information extraction from CAN-Bus for active safety systems, a time-window analysis was also performed showing that systems can be both long-term and short-term. In addition to this realisation, both generic and driver-dependent schemes were explored. From performance evaluation of the systems, generic system is found to be more appropriate scheme for manoeuvre recognition whereas the distraction detection is observed to heavily depend on driver and manoeuvre information. To demonstrate the future impact of this system, a utility analysis is also performed projecting the effect of this system on real accident data obtained from FARS accident data base (2009). First, a query is run on the FARS database to obtain the number of fatalities as the column, and several driver related factors on the rows. This table is rearranged into a more compact form and shown in Appendix A. In this table, categories of causation are grouped under three major groups: driver impairment, driver errors and in-vehicle devices. Refining these big groups into seven categories and matching them with potential CV systems appropriate to prevention of the accidents results in a new table shown in Appendix B. The refined categories are: driver impairment, poor decision making, reckless driving, poor lateral control, poor longitudinal control, poor manoeuvring and in-vehicle devices. The distribution of the database is shown in Figure 21. From this figure, it can be seen that only 34% of the fatalities are caused by driver related factors, however, 66% of the data is unclassified and therefore their cause is unknown. Therefore, we may say that 34% is an underestimated figure. Nevertheless, the distribution within this 34% of the fatalities in terms of causation give us important information about which types of driver errors can be prevented and where the drivers require the most assistance. From the distribution of the causation of accidents, we can clearly see that poor lateral and longitudinal control and manoeuvring accounts for up to 65%. Using only this figure, we can clearly see that driver assistance or active safety systems (DAS and AVS) can prevent at least 65% of accidents caused by human errors in poor manoeuvring or poor regulatory performance. The actual accident data is given in Appendix A.

**Figure 21** Driver-related factors in crashes and its distribution (see online version for colours)




In conclusion, this study has explored the capabilities of signal processing approaches in the CAN-Bus domain and proposed an intelligent module to recognise manoeuvres and assess the distraction/abnormality level of manoeuvres. Projecting the effect of this system on FARS accident data, 65% of human-caused accidents could be prevented if the proposed system could be used within vehicles. The authors hope that these encouraging results will attract more research in preventative active safety research using less explored but low-cost driver–vehicle interaction information from the CAN-Bus.

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## Appendix A

*Accident causation data from FARS database in 2007*

| *Categories of causation* | *Driver related factors (2) [FARS]* | *# of fatalities* |
|---|---|---|
| None | None | 52,976 |
| | Drowsy, sleepy, asleep, fatigued | 330 |
| | Ill, passed out, blackout | 130 |
| | Emotional (depression, angry, disturbed | 26 |
| | Medication, alcohol, drugs | 2,190 |
| Driver impairment | Inattentive (talking, eating, etc.) | 1,657 |
| | Road rage/aggressive driving | 42 |
| | Impaired due to previous injury | 6 |
| | Other physical impairment | 24 |
| | Mentally challenged | 7 |
| | Seat position not correctly adjusted | 3 |
| | Travelling on prohibited traffic ways | 8 |
| | Overloading or improper loading of vehicle | 110 |
| | Towing or pushing the vehicle improperly | 7 |
| | Failing to use headlights properly | 38 |
| | Operating without required equipment | 351 |
| | Following improperly | 223 |
| | Improper or erratic lane-changing | 219 |
| | Failure to keep proper lane | 8,645 |
| | Illegal driving on road shoulder, ditch, sidewalk | 32 |
| | Improper entry/exit (merging errors) | 34 |
| | Starting or backing improperly | 31 |
| | Passing through prohibited signs | 151 |
| | Passing with insufficient distance | 177 |
| | Failing to yield to overtaking vehicle | |
| Driver errors | Operating the vehicle in an erratic, reckless manner | 1,406 |
| | Failure to yield right of the way | 1,120 |
| | Failure to obey traffic sign, control devices or officers | 1,168 |
| | Passing through or around barrier | 13 |
| | Failure to observe warnings on vehicles on display | 27 |
| | Failure to signal the intentions | 24 |
| | Driving too fast, excess of the posted max speed limit | 7,327 |
| | Driving less than posted minimum | 11 |
| | Racing | 93 |
| | Making RT from LT lane or vice versa | 17 |
| | Other improper turn | 1,048 |

*Accident causation data from FARS database in 2007* (continued)

| *Categories of causation* | *Driver related factors (2) [FARS]* | *# of fatalities* |
|---|---|---|
| | Driving in wrong way, wrong side of the road | 331 |
| | Operator inexperience | 336 |
| | Unfamiliar with route | 84 |
| | Stopped in roadway | 33 |
| | Under-riding a parked truck | 5 |
| | Overcorrecting | 1,981 |
| In-vehicle devices | Cellular phone present in vehicle | 477 |
| | Cellular phone in use in vehicle | 77 |
| | Navigation systems | 7 |
| | Computer, fax, printer | 1 |

*Note*: Total number of fatalities in 2007 is 87,849.

*Source*: FARS (2009).

## Appendix B

*Recategorisation of FARS query for accident causation related to driver and potential CV systems for prevention*

| *Recategorisation of causation* | *Driver related factor [FARS]* | *# of fatalities* | *CV system* |
|---|---|---|---|
| None | None | 52976 | None |
| Driver impairment | Drowsy, sleepy, asleep, fatigued | 330 | EHT |
| | Ill, passed out, blackout | 130 | EHT |
| | Emotional (depression, angry, disturbed) | 26 | ER |
| | Medication, alcohol, drugs | 2190 | EHT |
| | Inattentive (talking, eating, etc.) | 1657 | EHT–ER |
| | Road rage/aggressive driving | 42 | None |
| | Impaired due to previous injury | 6 | None |
| | Other physical impairment | 24 | None |
| | Mentally challenged | 7 | None |
| Poor decision making | Seat position not correctly adjusted | 3 | None |
| | Travelling on prohibited traffic ways | 8 | None |
| | Overloading or improper loading of vehicle | 110 | None |
| | Towing or pushing the vehicle improperly | 7 | None |
| | Failing to use headlights properly | 38 | None |
| | Operating without required equipment | 351 | None |
| | Illegal driving on road shoulder, ditch, sidewalk | 32 | RAR |
| | Improper entry/exit (merging errors) | 34 | RAR–VDT–LT |

*Recategorisation of FARS query for accident causation related to driver and potential CV systems for prevention* (continued)

| *Recategorisation of causation* | *Driver related factor [FARS]* | *# of fatalities* | *CV system* |
|---|---|---|---|
| | Starting or backing improperly | 31 | VDT–PDT |
| | Passing through prohibited signs | 151 | TSR |
| | Passing with insufficient distance | 177 | VDT |
| | Failing to yield to overtaking vehicle | | |
| | Failure to yield right of the way | 1120 | VDT |
| | Failure to obey traffic sign, control devices or officers | 1168 | TSR |
| | Driving in wrong way, wrong side of the road | 331 | None |
| | Stopped in roadway | 33 | None |
| | Under-riding a parked truck | 5 | None |
| Reckless driving/inattention | Operating the vehicle in an erratic, reckless manner | 1406 | LT–OF |
| | Failure to observe warnings on vehicles on display | 27 | TSR |
| | Failure to signal intentions | 24 | None |
| Poor lateral control | Improper or erratic lane changing | 219 | LT–LCR–OF |
| | Failure to keep proper lane | 8645 | LT |
| Poor longitudinal control | Driving too fast, excess of posted speed limit | 7327 | OF–TSR |
| | Driving less than posted limit | 11 | OF–TSR |
| | Racing | 93 | OF |
| | Following improperly | 223 | OF–VDT |
| Poor Manoeuvring | Making RT from LT lane or vice versa | 17 | None |
| | Other improper turn | 1048 | None |
| | Overcorrecting | 1981 | None |
| In-vehicle devices | Cellular phone present in vehicle | 477 | None |
| | Cellular phone in use in vehicle | 77 | None |
| | Navigation systems | 7 | None |
| | Computer, fax, printer | 1 | None |