The feasibility of detecting phone-use related driver distraction

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Abstract: Apart from the driving behavioural change that can be the direct consequence of operating a car phone, phone-use related behaviour may also be a threat to traffic safety. Making notes or looking up telephone numbers while driving are example of such behaviour. In a driving simulator experiment 20 drivers drove in two conditions: under normal driving conditions and while being distracted because of telephone engagement. In the 'distracted' condition they had to handle a mobile phone while their attention was drawn off the road for up to several seconds by a telephone number search task. Results showed both a deterioration in driver performance on different vehicle parameters including behavioural (speed) compensation as a result of the demanding telephone task.

In an effort to develop an on-board detection system for this type of driver inattention, the data were used to serve as input for a real time diagnosis system based on Statistics, Artificial Neural Networks (ANNs) and Fuzzy Logic (FL). System performance in recognizing normal and deteriorated driving behaviour was 89%. On-line detection of driver distraction is considered feasible in the near future.

Keywords: Car phone; driving; distraction; evaluation; neural network; fuzzy logic.

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Karel A. Brookhuis (The Netherlands, 1950) studied experimental psychology at the University of Groningen, receiving his degree (Dutch Drs.) in Experimental Psychology in 1980. He was a junior research associate at the Institute for Experimental Psychology until 1983, specializing in psychophysiology. He completed a thesis on 'ERPs (Event Related Potentials) and information processing'. From 1983 on he was (and is) a senior research associate at the Traffic Research Centre/Centre for Environmental and Traffic Psychology at the University of Groningen, initially involved in research concerning drugs & driving. From 1994-2000 he was the institute's Research Manager. His current position is senior lecturer.

1 Introduction

Most studies performed with respect to car phones focus on the primary effect of car phones on vehicle control: the effects of dialling telephone numbers, effects of handling the phone itself and/or having a conversation (e.g. [1,2]). In general it is found that mobile telephone use increases variability in lane position and increases driver reaction time (e.g. [3]) However, apart from these effects that are a direct consequence of car phone use, there may also be more indirect effects. Behaviour that coincides with making telephone calls, such as looking up telephone numbers or making notes, might also threaten traffic safety, perhaps even to a larger extent. So far, however, research has not focused on these effects.

If driving behaviour is affected by car phone use, the question is what to do about it. In some countries (e.g. Spain) using a mobile telephone while driving is prohibited by law. Such a drastic measure could certainly prevent mobile phone related traffic accidents, but it also impedes possible positive effects of car phones, such as quick warning of the appropriate services in case of an emergency. Moreover, there are conditions in which making a phone call was found to have no detrimental effect on safety. For example, Brookhuis *et al* [1] found no negative performance effect of car phone use when driving on a quiet motorway. This is in sharp contrast with the results of an epidemiological study by Redelmeier and Tibshirani [4] where a four times higher risk of collision was found when driving and using a phone compared with driving without using the phone. A possible explanation for the differences between these two studies may lie in the fact that only a relation in time between making a telephone call and having an crash was established in the latter study, while the Brookhuis *et al* [1] study empirically studied the performance effects of using a car phone (e.g. vehicle control). The crashes may well have been caused by earlier-mentioned phone-use related behaviour such as looking up telephone numbers or writing down appointments (cf. questionnaire data on the relation between different sources of distraction and being involved in a crash [5]).

The SAVE project (System for effective Assessment of the driver state and Vehicle control in Emergency situations, Transport Telematics TR 1047) aims to detect deteriorated driver performance on-line. To attain this, a limited number of vehicle parameters such as headway, speed, steering wheel position and lane position are monitored and changes in these parameters can trigger warnings (see [6]).

The present experimental study focused both on the effects of driver distraction on vehicle control resulting from (secondary) phone task activities, and methods for detecting these performance decrements with an automated system. The present paper will focus on performance deterioration, compensation, and the feasibility of on-line detection of deteriorated driving behaviour. For an in-depth study of this method readers are advised to consult Hernández-Gress and Estève [7]. A more detailed report on the experiment itself can be found in de Waard, Van der Hulst and Brookhuis [8].

In this case, the real-time diagnosis system for automatic detection is based on a hybrid system involving statistical pre-processing, artificial Neural Networks and Fuzzy Logic [7]. Statistical pre-processing allows for data filtering and feature extraction. After that driving characteristics are learned, by an appropriate algorithm, the Generalized Radial Basis Functions (GRBF). The last step is the final decision by Fuzzy Logic in which a parametric learning method has been adopted. Here only an overview of the methodology will be given.

2 Method

Twenty subjects participated in the experiment that was performed in the driving simulator of the Centre for Environmental and Traffic Psychology of the University of Groningen, the Netherlands [9]. The driving simulator was a fixed base simulator consisting of a car body (BMW 518) with original controls and out-window graphics projection on a 165° panoramic screen. A graphical workstation (Silicon Graphics Skywriter 340 VGXT) generated the images. In this experiment drivers could drive freely on a two-lane road with a speed limit of 80 km/h. Other vehicles in the simulated world interacted with the simulator car and behaved according to hierarchically-structured decision rules that are based on a model of human driving behaviour [10].

At different intervals drivers had to answer a hand-held portable telephone and were asked to search for a telephone number on an alphabetically ordered list of 50 names and numbers, clipped on the dashboard. This task simulated the activity of looking up a telephone number from an address book. Subjects were asked to give priority to safe driving over performance on the telephone number-lookup task. This task had to be performed at some of the road segments while at other, control segments, no such task had to be carried out. At half of the segments a lead car was present. Subjects completed the test rides twice, once during the morning and once in the evening, resulting in a $2 \times 2 \times 2$ design (time-of-day, distracting task, lead car present). The order of conditions was balanced over subjects.

The following vehicle measures were sampled at 10 Hz and of these variables averages and/or standard deviation were calculated: speed, steering wheel position, lateral position and time-headway to a car in front. These parameters were tested using a repeated measures Analysis of Variance (ANOVA). A full list of parameters can be found in Table 1. In addition to these vehicle parameters, subjective ratings of mental effort (using the RSME, Rating Scale Mental Effort, [11], ratings of activation [12], and an evaluation of task performance on the Driving Quality Scale, [13] were collected. All three scales are unidimensional rating scales. These measures were taken to assess subjective experience of workload and activation, as well as to determine whether a possible deterioration in driving experience was performance as such.

Table 1 List of input variables

accelerator:	Accelerator pedal position (% depressed)
brake:	Brake pedal position (% depressed)
clutch:	Clutch pedal position (% depressed)
rpm:	Engine rotations per minute
velocity:	Speed (m/s)
steer:	Steering wheel position in degrees (0 is mid position, towards the left-hand side is positive)
latpos:	Lateral position on the road. The position of the mid of the vehicle (centre of the bumper) relative to the right hand line is indicated. The road width was 3 m.
thw:	Time headway to a vehicle (s) in front.
tlc:	Time-to-Line crossing(s). The time that is left before one of the lines (centre or edge line) is crossed if no corrective steering wheel movements are made.
ttc:	Time-to-collision (s).
leaddis:	Distance to a lead vehicle (m).
std_speed:	Vehicle speed standard deviation.
std_steer:	Steering wheel standard deviation.
std_latpos:	Lateral position standard deviation.

2.1 *General diagnosis system*

The general detection methodology as described by Hernández-Gress [14] includes three major stages:

1 Training of the diagnosis system using a pattern recognition approach. As input 'raw' vehicle data from vehicle sensors are used. In the training phase the system is 'told' by an input code when driving behaviour is impaired (i.e. a positive case). The first step in the training procedure is feature extraction. Its goal is twofold:

   - to remove noise and outliners from the original vehicle data set and,
   - to create new components based on the initial variables, as some of the input variables correlate highly. These new components are referred to as vectors.

   After this a specialized Neural Network is trained for each driving behaviour (in this case: normal and inattentive behaviour). The Final Decision of the system is made by using Fuzzy techniques [15].

2 Real-time diagnosis: the new components, the result of the training step, are used in real time to diagnose driver behaviour. Classification performance is increased by

maintaining the history of a certain time window (usually 300 data points when sampled at 10 Hz, but this depends on the general performance of the system, see [15].

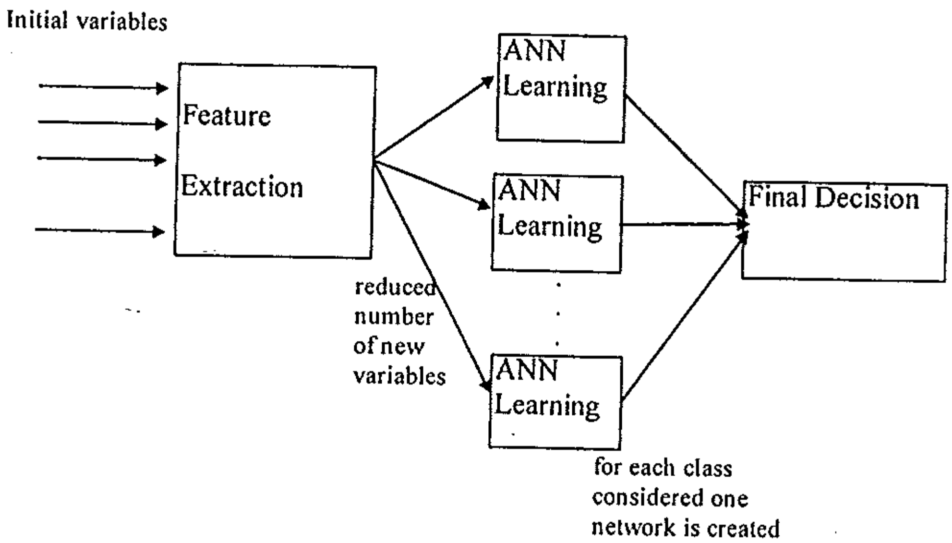
3 Evolution or customization: as driving skills vary greatly from one driver to another, individualization of the network is required [14].

In the chosen approach, driver behaviour will ultimately be diagnosed in real time. In the present study only the first stage (training) will be used. Both data with respect to normal and inattentive driving behaviour were used to train the system. Evaluation of system performance (i.e. automatic diagnosis compared with the evaluation of driving behaviour on the basis of performance variables) is accomplished off-line. System performance is operationalized in signal-detection terms (hits, false alarms, and misses).

2.2 *Training the diagnosis system*

The sets of patterns of normal and abnormal driving behaviour were processed by a group of statistical and artificial intelligence algorithms to perform a diagnosis by pattern recognition. First data were pre-processed by a non-linear feature extraction algorithm called Independent Component Analysis (ICA). Secondly, the new components were learned by a specialized algorithm called Generalized Radial Basis Functions (GRBF). Here each class is processed sequentially in order to map input patterns to the output decision space. The final step is the final decision in which Fuzzy Logic is used to increase the performance of the system due to the overlapping of the driving behaviours [16]. A schematic explanation of these procedures is presented in Figure 1.

Figure 1 The different modules of the training step. ANN = Artificial Neural Network



Feature extraction

The Independent Component Analysis (ICA) method was used to obtain a smaller number of variables from the initial set of variables. ICA is a non-linear method which can be viewed as an extension of the Principal Component Analysis method (PCA). It can be used to pre-process data before any type of classification. ICA searches a linear transform to minimize the statistical dependence between initial variables.

ICA is a non-linear decomposition algorithm which separates the independent sources q from an initial number of variables p (all variables sampled on-board are components of n vectors, and generally $q<p$). For an initial database X (n x p) the ICA algorithm performs blind deconvolution. Blind deconvolution methods are used to extract the sources from a set of (supposed) correlated observations. This is done to create new synthetic and independent variables from the initial data X keeping the most important and discriminating information while discarding irrelevant noise. A detailed explanation of the method can be found in [7].

Artificial neural network or learning of characteristics (Generalized Radial Basis Functions)

Generalized Radial Basis Function (GRBF) is a new technique which parameterizes a three layer Artificial Neural Network (ANN). The hidden layer is represented by a Gaussian activation function, while the last layer is a linear activation function that is not difficult to be learned because the hidden layer has linearized the problem. In these types of algorithms, activation of the hidden units is determined by the distance between the input vector and a prototype vector. The method consists of two steps. In the first step, the parameters governing the basis functions (corresponding to the hidden units) are determined using relatively fast, unsupervised methods. The second step of training involves the determination of the final layer weights, which requires a linear problem to be solved so as to achieve a very fast learning algorithm.

The parameters of the first layer (basis functions) are those that characterize a multidimensional Gaussian mixture (λ_k, μ_k, V_k).

As stated, a particularly important aspect is the distinction between the roles of the first and second weights layers. In the first step, we used the unsupervised algorithm called Expectation Maximization. The second part is left to algorithms of the Fuzzy Logic domain. The defuzzyfication is carried out by the maximum of the class (Unsupervised) and by learning.

The result of the first hidden unit can be seen as a membership function with a value between 0 and 1. A membership function is a real value between (0,1) representing to which degree a pattern belongs to a certain class. The closer the values to 1, the closer the pattern belongs to a class. In practice, one class is made of three or four basis functions. The aim is to describe as best as possible the cloud of points which represents the class while conserving the overlap of the class.

Final decision

With the help of fuzzy Logic (FL) a final decision on diagnosis is reached. Of particular importance is the overlap of classes, which may lead to false alarms. Fuzzy Logic features advantages relative to binary logic. Whereas with a normal classification point belonging to a class cannot be part of another one, Fuzzy Logic allows for the earlier mentioned membership degree to a cluster. Let one be denoted <premix> <<x is A>>, <<x is B>> where A and B are two different classes. X belongs to A and B with a membership degree μ_A and μ_B. Note that $\mu_i \in [0,1]$ and also $\sum_{i=1}^{c} \mu_i = 1$. These membership functions are used by a rule-based system like the Least Means Square approximation.

A membership function has been created using GRBF, and this function has values between 0 and 1. Then two different types of defuzzification techniques are used as final decision. These different techniques are the Maximum of the Membership function (MMF) and the Least Means Square Error (LMSE). In the present study with off-line analyses only the LMSE is used. MMF is used for real time diagnosis in which evolution is needed to improve diagnosis.

3 Results

3.1 Subjects

The average age of the subjects was 35 years (*sd* 7 years). They had held a driving licence for 14 years on average and drove 15,000 km/year on average.

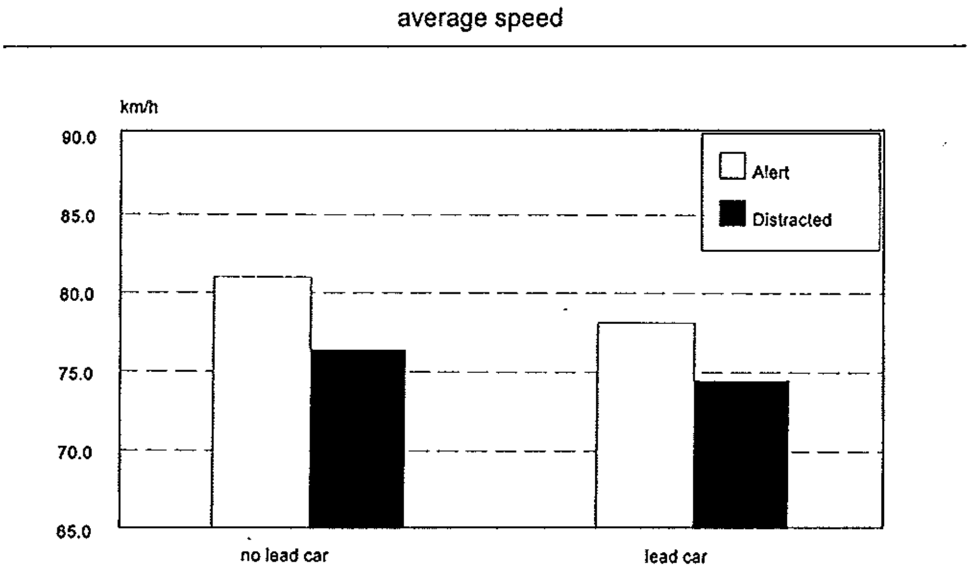
3.2 Driving behaviour and self-reports

Swerving seriously deteriorated as a result of the additional distracting task: the SDLP (Standard Deviation of the Lateral Position) increased from 0.22 to 0.29 metres ($F(1,18) = 30.7$, $p > 0.001$). The amplitude of steering wheel movements also increased dramatically as a result of the additional task, the standard deviation almost doubled ($F(1,18)= 66.4$, $p < 0.001$). Incidents, defined as crossing of the lane marking with two wheels, tripled as a result of looking up telephone numbers (see [8]). If there was a lead car present, driving speed was restricted to a maximum of 80 km/h and due to meeting traffic it was not possible to overtake lead cars. In conditions where there was no lead car, subjects drove faster than 80 k/h ($F(1,18) = 14.4$, $p < 0.001$), but only if they did not have to perform the secondary task (see Figure 2). The main effect of this distracting task is an average reduction in driving speed of 5 km/h ($F(1,18) = 6.18$, $p < 0.05$). As a result of this slower speed, time headway to a car in front frequently increased above five seconds, as the lead car did not slow down. According to Hogema and van der Horst [17] time headways above this criterion are non-following conditions. If time headways above this criterion are excluded from analyses, no effects on following behaviour are found ($F(1,12) < 1$, NS). Neither were any effects of time-of-day found on any of the driving performance parameters.

Self reports on mental effort, overall mental activation and driving quality were collected on unidimensional scales [11–13]. Self-reported activation and mental effort were significantly higher in conditions of the distracting secondary task (activation: $F(1,18) = 30.4$, $p < 0.001$, effort: $F(1,18) = 53.3$, $p < 0.001$). The effort rating increased from 'a little effort' in the normal driving condition to 'considerable effort' in the condition where drivers were distracted. The activation rating increased by some 20%

from 134 to 163 on a scale from 0 to 270. Drivers noticed their impaired driving behaviour, they rated the quality of their behaviour on a scale from -100 ('I drove very badly') to +100 ('I drove very well') as +9 in the normal driving condition, and as -42 in the distraction condition ($F(1,18) = 33.5$, $p < 0.001$).

Figure 2 Average driving speed (in km/h) during normal driving ('alert'), and while distracted by a telephone number search task ('distracted'). Two conditions are displayed, one without a lead car present and one with a car in front



3.3 *Detection of impaired driving behaviour*

The learning methodology (Feature extraction and GRBF and decision) as described above was applied to data of 16 subjects whose data sets were complete (see Figure 1 for the sequence of algorithms). Fourteen variables in total, listed in Table 1, were used as input variables.

After the first phase, feature extraction, eight independent components were kept. The correlation of these new components with the original variables were as follows (see also Table 1):

Independent Component 1: accelerator + 0.9; brake -0.7; clutch -0.8; rpm +0.9; velocity +0.8

Independent Component 2: thw -0.9; leaddis -0.9

Independent Component 3: steer -0.7; latpos +0.8

Independent Component 4: std_steer +0.8

Independent Component 5: std_speed +0.8

Independent Component 6: std_latpos -0.7

Independent Component 7: tlc -0.7

Independent Component 8: ttc +0.6

The first component reflects speed control and uses five variables (accelerator, brake, clutch, rpm, and velocity). The second component reflects headway control, and the third component reflects lateral position control. Components 4, 5 and 6 are based on standard deviations of variables that are not correlated with other variables. The same applies to TLC (Time-to-Line Crossing) and TTC (Time-To-Collision).

For each subject, the training step was carried out with normal driving and deteriorated performance data. The eight new components plus a target (1 = using the phone/0 = normal) were used to train and to test the learned data base. Fifty percent of the data were used to build the system and the other 50% were used to test the system. In this way each system is personalized to the driver and evaluated using vehicle data of the same driver. Then for each subject, learning and final diagnosis were performed so as to evaluate the system's performance.

In Table 2 overall performance stands for correct driver behaviour diagnosis per subject ('hits', the number of times the system diagnosed normal behaviour as normal and impaired as impaired). Misses are classified as 'normal' while subjects driving performance was actually impaired by using the phone. False Alarms are classified as impaired while the driver was driving normally.

Table 2 Classification performance for the 16 individual drivers in the experiment whose data set was complete

Subject Number	*Overall Performance (%)*	*Miss (%)*	*False Alarms (%)*
01	87.3	3.7	9.1
02	95.2	0.7	4.1
03	85.0	6.4	8.6
05	90.3	1.6	8.0
06	85.6	6.9	7.5
07	87.8	1.9	10.4
08	91.3	0.1	8.6
10	96.7	0.5	2.8
11	97.8	0.2	2.0
13	89.3	2.0	8.7
15	93.1	2.1	4.9
16	85.4	7.5	7.2
17	84.2	7.3	8.5
18	89.5	3.2	7.3
19	87.0	5.7	7.4
20	85.5	6.2	8.3
Total	89.3	3.5	7.1

4 Discussion

Compared to direct effects of car phone use (see e.g. [1]) phone-use related effects such as handling a phone and looking up a telephone number clipped on the dashboard while driving have been shown to have a serious effect on lane-keeping performance. Swerving increased dramatically, while driving out-of-lane increased by a factor of three. In recent years impaired driving behaviour has been linked to exceeding critical values of performance [18]. In the present experiment these critical values were exceeded for lateral position control (set at 0.25 metres, measured was 0.29 metres) and steering wheel movements (the critical value for the standard deviation of steering wheel movements was set at 1.5° while here in the distracted condition the average was 3.5°). The effects on lane-keeping remain clear even if drivers, when performing the demanding secondary task, compensate (at least to some extent) for the deterioration in performance by reducing speed and increasing the distance to a car in front. This behavioural compensation is not uncommon and has been observed more frequently, e.g. when subjects had to adjust a stereo [19], when they had a conversation [2], or when they were fatigued [20] they slowed down and increased their safety margins.

Automatic on-line detection of driver distraction seems feasible. The system is able to notice and differentiate between normal and impaired driving behaviour and diagnose these as such. The performance of 89% is very good since this diagnosis is based on each sample of data, which means an evaluation every 10 ms. The final diagnosis will be based on 30 seconds of data or more. It is expected that in this way the hit rate will increase and, most important, false alarms will be reduced to a minimum.

5 Conclusion

Before a car phone is actually used, sometimes telephone numbers have to be looked up. This task, looking up telephone numbers while holding the phone in one hand showed a serious deterioration in driving performance in terms of lane control. This effect was clearly present despite the fact that drivers increased their safety margins by slowing down. It was shown that on the basis of several vehicle parameters impaired driving could be detected automatically with a hit rate of almost 90%. Future research should focus on how to minimize false alarms (now 7%) and a possibility for success lies in using longer, e.g. 30 seconds segment of data as input for the evaluations.

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