

# Modelling Driver Intention and Behaviour at Roundabouts

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**Abstract:** This paper focuses on modelling driver intention and behaviour at roundabouts in order to provide information on whether or not a driver intends to leave the roundabout when approaching an exit of a roundabout. Advanced Driver Assistance Systems' effective work depends on adequate driving intention recognition and behaviour prediction, so if the driver intention and behaviour at roundabouts can be modelled and predicted, the roundabout safety and efficiency can be significantly improved. As the driver intention recognition is basically a pattern recognition problem, the machine learning theory is a good candidate for training models. The data for training and validating the models have been planned to be gathered from both the laboratory controlled simulation and field study.

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It was reported in November 2013 that a cyclist in her mid-20s had died after being hit by a lorry at London's Bow roundabout (Cyclist dies in Bow Roundabout lorry collision, 2013). When the collision occurred, the driver of the lorry thought that the cyclist was travelling in the same direction with him. There are many other similar crash accidents happen every year at roundabouts (Brilon, 2005). One possible solution for decreasing the accidents and improving the roundabout safety is to warn the ego drivers with Advanced Driver Assistant Systems (ADASs) when he/she seems to overlook the potential risk. To get this goal, the ADASs need to figure out what the drivers intent to do in advance. The aim of the work presented in this paper is therefore to recognize driver intentions when driving through a roundabout and to predict the driver behaviours. This paper is organized as follows: Section 1 introduces the motivation of this study, state of the art, the research gap and questions addressed. In section 2, the plan for empirical studies and data collection are described. Section 3 introduces the idea of data processing and modelling for driver intention recognition and behaviour prediction, and lays out a plan to validate the performance of the classification methods and the behaviour models and to demonstrate the models' prediction ability. Finally, section 4 concludes this paper and presents the plan for future work.

## 1. INTRODUCTION

### 1.1 Motivation

Roundabout is an essential component of road infrastructure that has gained significant importance in recent years in many countries. In France, the number of roundabouts increased from 500 to 25,000 in twenty years till 2005 (Guichet, 2005). According to Baranowski's report (2013), till 2013, there were up to 32,000 roundabouts in France and

estimated 25,000 roundabouts in the UK, and the number of modern roundabouts in the USA has increased by around 3,700 in the past twenty years. Compared to signalized intersections, roundabouts have been shown to reduce the total number of injury crashes by 76% and the total number of fatal crashes by more than 90% (Montella, 2011). However, the absolute number of crashes at roundabouts was still high according to Montella's study (2011) of crash data from 15 urban roundabouts located in Italy. The analysis, investigating the period from 2003 to 2008, showed 274 crashes occurred in total and the different types of these crashes, see Fig. 1 and Appendix A. In almost one-third of the crashes a contributory factor related to the road user was identified, with the failure to give way being the main one. For instance, the indicator was set for only 80% of all turn manoeuvres (Auto Club Europa, 2008). Therefore, we deem that it is an important contributing factor to accidents that drivers indicate their intention to leave or stay in the roundabout incorrectly, or make incorrect predictions for the behaviour of other drivers for the same reason.

In order to prevent or mitigate the effects of this kind of accidents before they happen, a possible method would be to warn the ego driver with Advanced Driver Assistance Systems (ADASs) when he or she seems to have overlooked the potential risk. ADASs have become an integral component of modern vehicles nowadays (Hummel, 2011). Aiming at effectively improving driving safety and comfort, they need to understand the driver's intent and choose a suitable control strategy to assist or warn the driver (He, 2012). However, the driver intent recognition in the roundabouts is still a currently open question in the field of driving safety study.

Thus, this study aims to infer driver intention and model the driver behaviour when approaching the exit of roundabouts, in order to help ADAS correctly understand and

appropriately assist and warn the driver. Consequently, roundabout safety and efficiency can be improved.

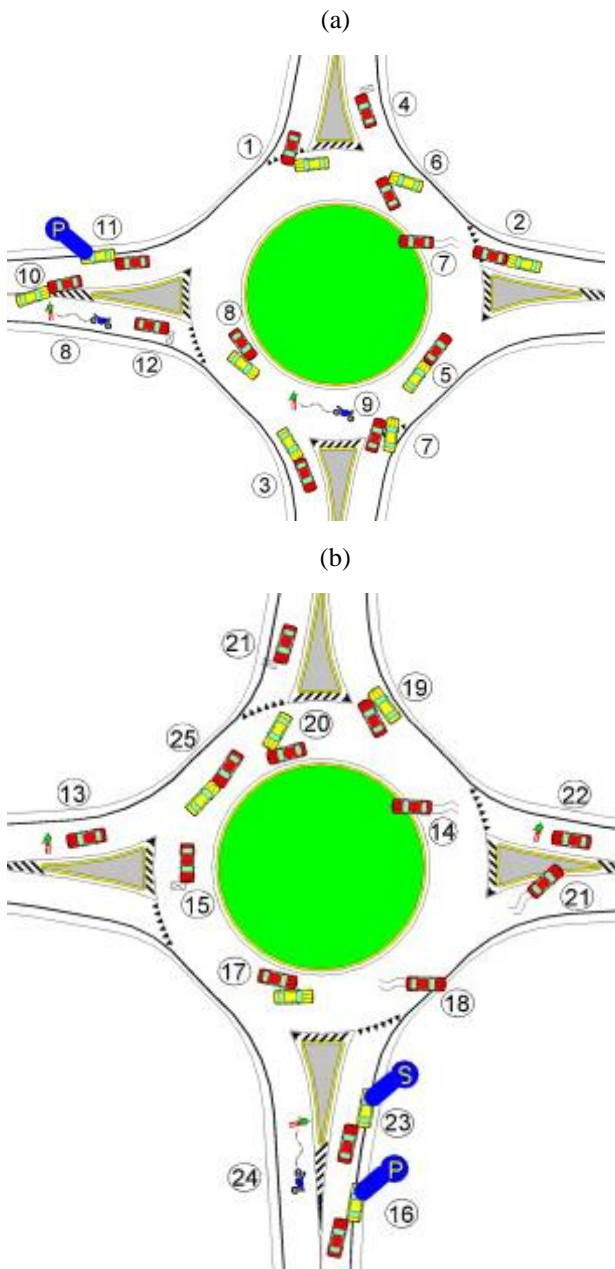


Fig. 1. Crash types at roundabouts (Montella, 2011).

## 1.2 State of the Art: Intention Recognition

### 1.2.1 Situation

The driver intention recognition for car following and lane changing has been investigated a lot. Drivers' intended actions can be identified before the actual execution by observing the driving movements (Liu, 1997) and eye motion (Land, 1999). Pentland (1999), Kuge (2000), and Mizushima (2006) all proposed prediction models for lane changing behaviours on highway using Hidden Markov Models. Their methods assumed that human intention was a sequence of internal mental states that could not be observed directly but modelled through abstracting the observable

behaviours with HMMs. Pentland's recognition system could predict changes in the first 0.5 second of the manoeuvre. Kuge and Mizushima all proposed a continuous recognition system using steering wheel features.

Similarly, Tango (2009) classified the lane changing/car-following manoeuvre with three machine learning techniques, which were Neuro Network, Hidden Markov Model, and Support Vector Machine (SVM), using steering angle, speed of the vehicle, lateral position, jerk (first derivative of acceleration) and time to collision as inputs. Then the modelling performances for different methods were compared.

Last, Möbus and Eilers (2011) developed a Bayesian Autonomous Driver Mixture-of-Behaviours (BAD MoB) model for the longitudinal control of human drivers in an inner-city traffic scenario.

Driver intention inference for urban intersections has also been an important research topic for the many years. The driver turning behaviour at intersections was predicted by Naito (2008) using K-means clustering. Lefèvre (2011) proposed a Bayesian network which combined probabilistically uncertain observations on the vehicle's behaviour and information about the geometrical and topological characteristics of the road intersection in order to infer a driver's manoeuvre intention. Aoude (2011) developed methods to classify the driving manoeuvres at intersections using Support Vector Machine and Hidden Markov Models. Liebner (2013) proposed a Bayesian network model to infer the driver intention at urban intersection in the presence of preceding vehicles. In his study, a parametric model to represent both car-following and turning behaviour was considered. Gadepally (2014) estimated driver decisions near intersections using Hidden Markov Model, based on modelling the driver behaviour and vehicle dynamics as a hybrid-state system (HSS).

### 1.2.2 Methodology

From literature, machine learning approaches have been demonstrated to outperform other modelling approaches in such situations. Based on the intrinsic ability to discover and learn knowledge from large amount of available data, the machine learning techniques have attracted much attention in pattern recognition, data mining and information retrieval. In addition, it could provide some theoretical analysis and practical guidelines to refine and improve the recognition performance (Chao, 2011). For this reason, several machine learning techniques are summarized in this paper.

#### a. Support Vector Machine

Support vector machine (SVM) is a classification and regression method for analysing and recognizing data. SVM emerged in mid-1990's from the area of statistical learning theory developed by Vapnik in the late 1970s, and were widely used in many areas, such as handwritten digit recognition (Cortes, 1995) or object recognition (Blanz, 1996).

The main idea of SVM is to map data to a higher dimensional space, where the two categories are more easily separated with a kernel function, see Fig. 2. Then, training data is separated with the hyper-plane which can be identified by solving an optimization problem. The hyper-plane is based on support vectors, which are a set of boundary training data. New data are classified according to which side of the hyper-plane they fall into. For a given set of data, there can be more than one hyper-plane. The goal is to find a hyper-plane that maximizes the margin between these two classes. The margin is defined as the sum of distances from the closest data points of both classes to the hyper-plane, see Fig. 3. A larger margin is necessary because it reduces the over-fitting problem. Over-fitting occurs when the solution is too customized for the training data and not generalized for new data (Bengtsson, 2012).

SVM has many advantages. First, it works well with small sets of training data and a large number of inputs (Cortes, 1995). Second, SVM is robust to the over-fitting problem by using a cost function for finding a large classifier margin (Bengtsson, 2012). At last, other mathematical approaches are also allowed to be incorporated into SVM. For example, it can be extended to include fuzzy sets, thereby capturing real-world uncertainty with each point belonging to different classes to some degree (Tsang, 2003).

However, SVM also have some disadvantages. One issue is that the method does not incorporate temporal variations like Hidden Markov Models do. Besides, it is difficult to choose good kernel and regularization parameters (Mandalia, 2004).

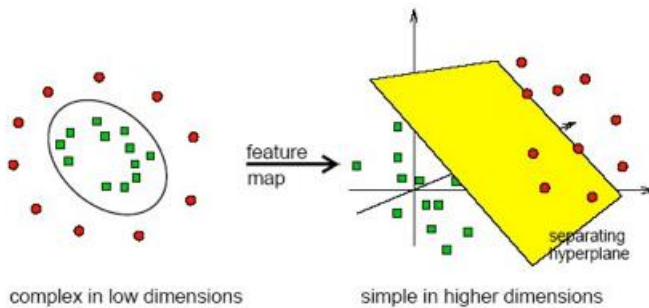


Fig. 2. Comparison of low dimension and higher dimension (Chang, 2001).

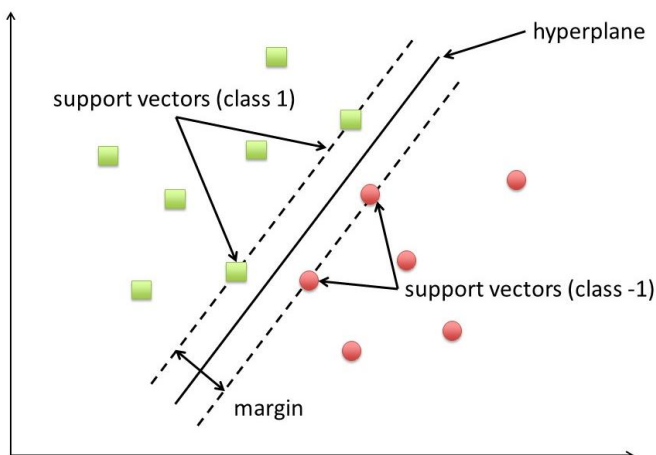


Fig. 3. Data sets separated by hyper-plane.

### b. Hidden Markov Models

Hidden Markov Models (HMMs) describe a probability distribution over a number of possible sequences which is composed of a number of hidden states and a number of observations (Fig. 4). The sequence of states is a Markov chain, which means the knowledge of the previous states is irrelevant for predicting the probability of subsequent states. Starting from some initial state, a sequence of states is generated by moving from state to state according to the state-transition probabilities. Each state then emits observations according to the state emission probability distribution (Rabiner, 1989).

HMM is a good method for recognizing human intention for two reasons. First, HMM support recognition of temporal data patterns. This is important because humans perform different actions on a variable time-scale. Even within a simple manoeuvre the internal states may vary in time. HMM provide an excellent framework for such temporal mappings. Second, human actions can be observed as the result of some sequence of internal mental states and can be used for referring the hidden states. (Mandalia, 2004).

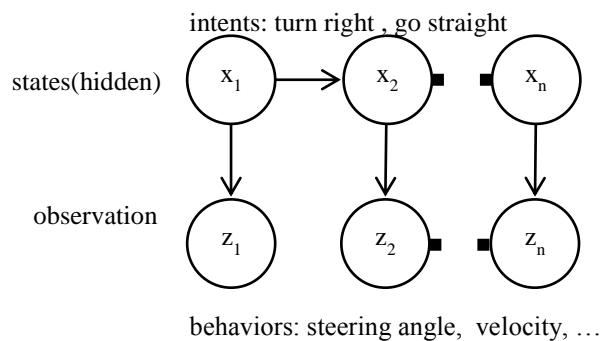


Fig. 4. Example structure of a Hidden Markov Model.

### c. Artificial Neural Networks

Artificial Neural Networks (ANNs) are learning algorithms inspired by biological neural networks and are used to estimate functions with a large number of inputs (Yegnanarayana, 2009). They are composed of a number of very simple processing elements, known as neurons. These elements compute an output dependent on the values of the inputs using an internal “transfer function”. The neurons are joined together by weighted connections, along which data flow, being scaled during transmission according to the values of the weights (Yella, 2006).

An ANN consists of layers which are the input layer, the hidden layers and the output layer (Fig. 5). The input layer consists of all input factors. Information from the input layer is processed with one or more hidden layers as intermediate layers between the input and output layers, then, the output vector is computed in the output layer (Akgüngör, 2009).

In driver behaviour research, ANN is an attractive choice for prediction of the future trajectory because it can learn from

the data available in a supervised way. Such a Neural Network is an adaptable system that can learn knowledge with repeated presentation of data available and then generalize the new data. If we give the Neural Network a set of input values and corresponding output values, it will try to learn the input-output parameter relationship by adapting its weights (Tomar, 2010). Therefore, the driving path prediction can be realized by Neural Network based on the available trajectories data of different drivers although the path is influenced by a large number of factors (Malta, 2009).

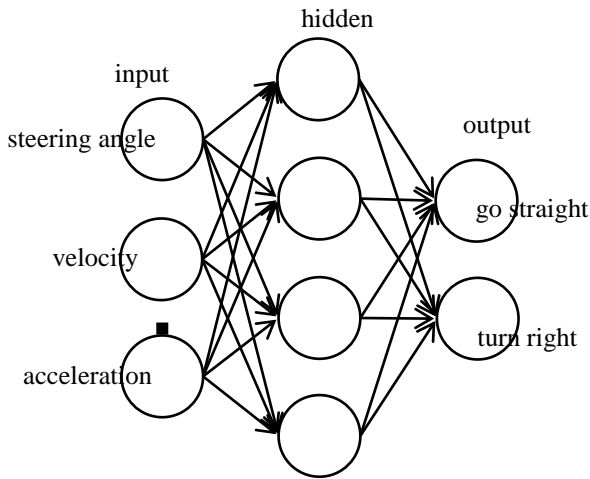


Fig. 5. Diagram of a simple network

#### d. Comparison

According to Tango's (2009) research for the classification of car-following manoeuvres, ANN achieved performances comparable to SVM, and the main difference was the computational time taken for learning. In the case of SVM, this process took typically less time than for feed-forward Neural Networks, but once the network was trained, its response time was shorter than that of a SVM. In contrast, HMM could solve the multi-classification problem in a quite natural way, and provided also rather good results in the distinction between the case when manoeuvre was present and when not.

However, these results are all about the application in the situation of car-following manoeuvre, and the choice of one technique rather than another is strongly depending on the specific application to implement. In this study, HMM is chosen because its characteristics for a time series of observation/states match natural human behaviour/intention.

#### 1.3 Research gap

The driver intention recognition in common driving manoeuvres such as car following and lane changing has been investigated much more than the manoeuvres at roundabouts in the past decades. Mudgal (2014) proposed the model of speed profiles at roundabouts using a Bayesian inference methodology and simulated the circulating speed and maximum accelerations. Yet no method for inferring driver intention and behaviour at roundabouts was developed.

Therefore, this study focuses on inferring the driver intention and behaviour when approaching the exit of the roundabout.

#### 1.4 Research question addressed

In principle, the question addressed in this paper is how to recognize two possible driver intentions at roundabouts and then how to predict the future driving behaviours, such as the velocity and track of the vehicle in a few seconds. The two possible intentions can be defined as follows (cf. Fig. 6):

- 1) continue driving in the roundabout (going straight)
- 2) take the exit to leave the roundabout (turning right)

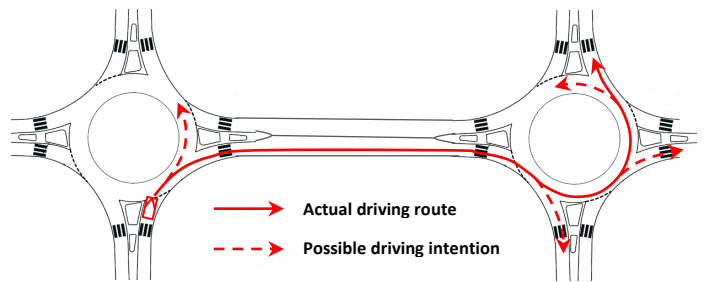


Fig. 6. Illustration of driver intention in the roundabouts.

Therefore, the intention recognition here is a binary classification problem, which means we can use the driving behaviour data and corresponding known intentions to train a model in a supervised way, in order to make the model can divide the data for two different intentions into two different classes. Then, the model can predict the unknown intention through estimating which class the data belong to.

In order to train the driver intention models based on Machine learning techniques, the observation in this study will be collected which includes vehicle behaviour, driver eye movement and the traffic situation:

**Vehicle behaviour:** the kinematic behaviour of the vehicle, including steering angle velocity, steering angle, velocity, acceleration, and position.

**Driver eye movement:** Driver eye movement has been identified to be a relevant feature for driving manoeuvre prediction and intention recognition, especially combined with the vehicle behaviour (Lethaus, 2011).

**Traffic situation:** the different layouts of the roundabouts have been taken into account to interpret the vehicle behaviour and estimate the driver intention.

After acquiring the observation data in the simulation as well as in the real traffic, the first step of the recognition procedure should be to pre-process the original data and to extract the features. Then, for each manoeuvre (to continue driving in the roundabout or take the exit to leave it), the appropriate HMM structure will be chosen and the model will be trained based on those features and initial sets of parameters. At last, the probability of each model given the observation of real driving will be calculated and the model that outputs the maximum probability will be the current

manoeuvre. Since the observation is a dynamic time series of data set, the intention will be inferred online.

## 2. EMPIRICAL STUDY AND DATA COLLECTION

The empirical study includes simulation in the laboratory and real driving in field study. Both parts are necessary in order to improve the internal and the external validity. Internal validity, which is the approximate truth about inferences regarding causal relationships, requires controlling influences that may impact the relation between causal variables and effect variables. External variables enables generalizing across situations and drivers (see e.g., Trochim, 2001). The laboratory study focuses on the internal validity; the field study focuses on the external validity. In the field study, the driver behaviours are natural but effected or intervened by too many factors, which means the observed changes are not necessarily attributable to the important causes, resulting in a low internal validity. As complement, a simulation experiment is conducted in the laboratory, where the experimental condition can be controlled and undesired disturbances eliminated.

### 2.1 Simulation study

The simulation study is planned to be conducted in a controlled, laboratory setting to gather data on the behaviour of drivers at roundabouts. The roundabouts experimentally vary among four different layouts (number of arms being either 3 or 4, with an inscribed circle diameter of 25 m or 40 m). Around twenty drivers will repeatedly drive in a driving simulator and follow a standardized route with those four different types of roundabouts. While the drivers are carrying out the driving task, their gaze behaviour and the driving behaviours (steering angle, steering angle velocity, acceleration, velocity, and position) will be measured.

### 2.2 Field Study

A field study will be conducted as well to ensure that the hypotheses developed in the laboratory is still valid in the real driving. During this field study, at least five drivers will drive through a standardized route in the city of Braunschweig, Germany. The drivers will be given instructions of which exit to take before entering the roundabouts. This route contains three roundabouts that resembled the three used in the laboratory study. Also in parallel to the laboratory study, information on the drivers gaze behaviour and driving behaviour will be collected. The study will be conducted at the weekend in order to get the data for free driving and during the week to get the data for driving with other traffic.

The data will be acquired using the ViewCar, which is an equipped vehicle dedicated to the analysis of driver behaviour and cognition in real traffic (Fig. 7). It is equipped with sensors to gather data about traffic, the state of driver, and vehicle guidance, in order to help understand and model

the driver behaviour. The position of the automobile is measured using differential GPS. Smart eye software records the driver's gaze direction. The driving environment information will be recorded by front, rear and side cameras, and the video information will be analysed manually in order to identify the manoeuvres driven.

During the preliminary field study, some rough data have been gathered when the driver was driving through the three roundabouts in Braunschweig. The driver was instructed to take every pair of entry and exit for all the roundabouts and the related data have been logged. According to the analysis of these rough data, the field study plan will be improved.

(a)



(b)



Fig. 7. The equipped research vehicle ViewCar.

## 3. MODELLING AND VALIDATION

Data processing is the first step for modelling. It includes data cleaning, normalization, transformation, feature extraction and selection (Kotsiantis, 2006). The data will be split randomly into a training set and a validation set. These two data sets will be filtered in order to be clean and reliable enough for training and validating models effectively. Then separate the training data set into two parts for going straight and turning right, in order to train the different models for different intentions. We will compare the driving data with the simulated behaviours generated by the different two driver intention models and to estimate the posterior probability of each hypothesis. The probability distribution

can be used to predict the driver's intention and the future driving behaviours (Liebner, 2013).

After modelling the driver intention and behaviours, the models performance requires validation and comparison with real human behaviours. Since the gathered data will be split randomly in training set and validation set. The validation data set can be used as inputs for the models to compute the output, and then the output will be compared with the real data as an evaluation for the models. At last, according to the comparison results, the design of the empirical studies and the methods of intentions recognition models can be improved.

#### 4. CONCLUSIONS AND FUTURE WORK

This study focuses on the driver intention recognition and driving behaviour prediction at roundabouts. In the course of this analysis, we have developed a preliminary study for this goal, including the empirical study design and preparation, the study of machine learning techniques, and the plan for modelling process. The further step for this study is to acquire driving data measured with the driver simulator and the equipped testing vehicle ViewCar. Meanwhile, the modelling methods, such as HMMs, should be studied more deeply in order to establish a structure for describing driver behaviour appropriately. Finally, it is need to be proved that the models we will develop can recognize the driver intention at the roundabouts effectively and early enough and predict the driving behaviour precisely.

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Appendix A. CRASH TYPES AT ROUNDABOUTS  
(Montella, 2011)

Rank	Crash type	Crash number
1	Entry – angle	57
2	Entry – rear-end	31
3	Exit – rear-end	17
4	Exit – hit obstacle in carriageway	14
5	Circulating roadway – rear-end	13
6	Exit – angle	12
7	Entry – sideswipe	12
8	Entry – falling from a vehicle at entry	11
9	Circulating roadway – falling from a vehicle	11
10	Entry – head-on	10
11	Exit – hit parked vehicle	10
12	Entry – hit obstacle in carriageway	8
13	Exit – hit pedestrian	7
14	Entry – run-off-the-road	7
15	Circulating roadway – hit obstacle	7
16	Entry – hit parked vehicle at entry	7
17	Circulating roadway – sideswipe	7
18	Circulating roadway – run-off-the-road	6
19	Exit – sideswipe	6
20	Circulating roadway – angle	5
21	Exit – run-off-the-road	5
22	Entry – hit pedestrian	3
23	Entry – hit stopped vehicle	3
24	Exit – falling from a vehicle	3
25	Circulating roadway – head-on	2