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Development and evaluation of a advanced driver assistance system

A 3D auditory in-vehicle advisory interface for traffic information presentation

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Chenhui Hong

Department of Signals and Systems
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2016

Master's thesis 2016: EX083/2016

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Supervisor: MinJuan Wang, Department of Applied IT
Martin Fabian, Department of Signals and Systems
Examiner: Martin Fabian, Department of Signals and Systems

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Department of Signals and Systems
Division of Control, Automation and Mechatronics
Automation
Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

Cover: Sensor to the road users, resource from the Volvo Car.

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Abstract

Keywords: auditory advisory, traffic information, behavior modeling, process mining, data mining.

Driver safety continues to be hugely important to car manufacturers, governments and drivers. Statistics from the CARE European Road Accident Database (2012) reveal that there were 1,190,448 accidents and 34,817 fatalities in Europe during 2009.

Recently, researchers have pointed out that Advanced Driver Assistance Systems (ADAS) should focus more on design for situational awareness to provide the driver with attention supports. The studies carried out by M. Wang have proved that providing continuous visual traffic information increased drivers' safety during highway scenarios. In addition, drivers perceived the information as non-obtrusive. Studies found that early warnings or normal driving information presentation reduced the number and severity of crashes. Recent studies on auditory modality in vehicle use has also shown great potential that auditory information may be more effective than visual modality. Results of studies have proven that auditory information improve safety in driving, shorten response time, enhanced accuracy and increase drivers' situation awareness.

To verify the effects of the auditory advisory system, data with respect to the drivers' behavior collected from experiments need to be analyzed and evaluated. Process mining, i.e., extracting valuable, process-related information from the event logs, complements existing approaches to Business Process Management (BPM). BPM primarily focuses on analysis of process management and the organization of the work from process automation and process analysis, and aims to improve operational business processes, possibly without the use of new technologies. On the other hand, BPM is often associated with software to manage, control and support operational processes. As BPM heavily relies on process models, process mining plays a very important role in raw data analysing. Process mining which focuses on processes but uses the real data is bridging the gap between classical process model analysis and date oriented analyses like data mining and machine learning.

In this case, related to the driving behaviour, data like steering wheel angles, velocities, accelerations, reaction times, longitudinal/lateral position and etc. will contribute to build model to illustrate how drivers will behave with and without the auditory advisory system in different scenarios.

The objective of this thesis work is to develop and verify a 3D auditory advisory traffic information system (3DATIS) based on design requirements generated from previous studies and investigate the conceptual design for its safety value and possible positive/negative adaptive behavior of the drivers to 3D sound information presentation in a car simulator.

This report presents how we design the 3DATIS system and illustrates how it influences drivers' behavior.

Acknowledgements

This master's thesis was carried out at SAFER, Vehicle and Traffic Safety Center at Chalmers, in Gothenburg.

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Last but not least, I give gratitude to my family, for your support and company during my studies.

Chenhui Hong, Gothenburg, October 2016

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1
Introduction

In this chapter, the background of the thesis goal and the related works will be introduced.

1.1 Background

Road transportation by use of vehicles enables nations as well as individuals to reap the benefits of the movement of goods and people. The benefits could for example be the access to better jobs, markets, health care and education. However, with an increasing number of automobiles on the road, the traffic situation is becoming more and more challenging for the drivers. According to the World Health Organization (WHO), road traffic accidents caused approximately 1.25 million worldwide death in 2015[1]. That is to say, in every minute, 3 people were killed in traffic accidents. Predicted by WHO, in 2030, the road traffic injures will go up to rank 5 in the list of leading causes of death from 2.2% to 3.6% which will exceed lung cancers, tuberculosis, HIV, and diarrhoeal diseases[2].

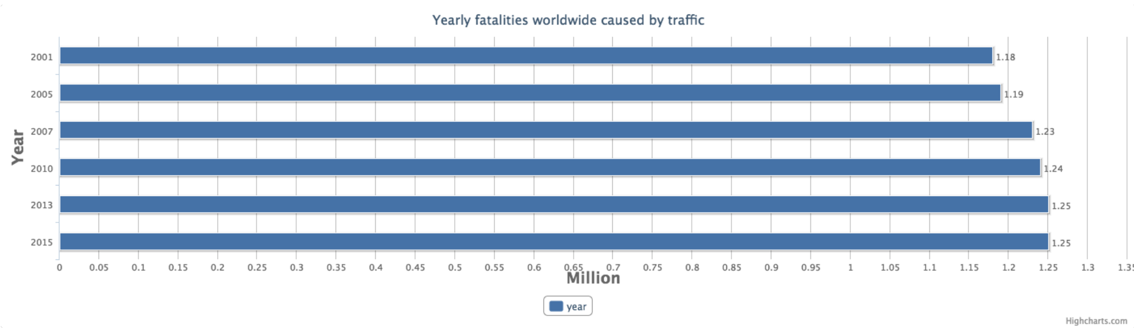


Figure 1.1: Worldwide number of road traffic deaths

As illustrated in figure **??**, the worldwide number of road traffic deaths was increased in the past decade. However, during the same period the world population increased by 5% [1]. Furthermore, from 2010 to 2013 the number of registered automobiles increased by 16% worldwide[1]. This demonstrates that in the past years, the road safety efforts have saved lives. Hence, driver safety continues to be hugely important to car manufacturers, governments and drivers.

Active and passive safety systems are two primary safety systems which are used in vehicle industry nowadays for reducing the effects of collisions. For instance, seat belts and airbags are two well known examples of passive safety systems which protect passengers to avoid injures after the collision happens. Active safety systems on the other hand are used help drivers to understand the state of the automobile to both avoid and minimise the effects of a crash.

Active systems today fall under the general term of Advanced Driver Assistance Systems (ADAS). Increasing demand for ADAS is seeing new generations of cars equipped with numerous sensor technologies powering the aforementioned systems. In the past decades, the early ADAS designs only focused on the warning zone which means the warning voice would give to the drivers less than 2.5 seconds. Such a time will give the drivers shortest time to react to the emergency events in order to avoid the collision happen, according to T.J. Triggs et. al [3].

However, unnecessary information presented to the driver can lead to high visual attention and mental workload. Furthermore, a lot of the traffic information presented from ADAS are warning signals that are usually activated in potentially dangerous near-crash and pre-crash situations. The playing of a warning voice only make sense when a crash is going to happen immediately. Also, the frequency of warning should be rare as well. Otherwise, it could cause 'cry wolf' effect which makes the drivers neglect the warning for the real potential risk and fail to follow the designed reaction.

Hence, in the next step, the ADAS system shifts to a 'higher' level which provides advisory information rather than warnings. Those particular forms of ADAS are called *Advisory Traffic Information Systems (ATIS)*, and they support decision making on a longer time scale, i.e. on the tactical and strategically levels, as opposed to on the operational level.

1.2 Advisory Traffic Information System (ATIS)

According to Summala[5], the aim of drivers is to drive in their comfort zone. While the border of the comfort zone is surpassed and thus the safety margin violated, the drivers will feel uncomfortable and try to adapt their behaviors to corrective actions. To maintain comfortable driving, drivers require more information from the surrounding traffic environment which makes it possible for them to handle the potential risks. How can the surrounding information be sent to the drivers effectively to support them in some ways that they feel comfortable?

The studies carried out by[8] have shown that providing continuous visual traffic information increased drivers' safety during highway scenarios. In addition, drivers perceived the information as non-obtrusive. Studies found that early warnings or normal driving information presentation reduced the number and severity of crashes [6].

M.Wang et al. [6] pointed out that the visual traffic advisory system can help make the behaviors of drivers 'safer' in comparison to a reference group in some specific traffic scenarios. The number of collisions can also be reduced significantly.

1.3 Hypothesis

Recent studies on auditory modality in vehicle applications has shown great potential and illustrated that auditory information may be more effective than visual modality. Additionally, the results of other studies have shown that auditory information improves safety in driving, shortens response time, increased accuracy and improve the situational awareness of drivers[3][4][8]. Hence, in this thesis we would like to find a way how to express and research the auditory information in order to improve the behavior of the driver of the vehicle with respect to safety and reliability.

1.4 The main research questions

The objective of this thesis work is to design and verify the 3D auditory advisory traffic information system (3DATIS).The performance of the system will be investigated based on the safety value and the possible positive or negative adaptive behaviors of the drivers when subjected to the 3D sound information. The driving tests will be carried out in a car simulator.

The master thesis shall answer the following questions:

• How to design the 3DATIS?
1. How to play the voice?
2. What kind of melody should be used?

• How do 3DATIS influence driver's behaviors?
1. What kind of data need to be collected?
2. How does the data have to be processed to be able to build from it a model of the driving process?
3. How then to from that data build process models of different scenarios?

• In which stages will 3DATIS have a noticeable effect, either positive or negative?
1. What kind effect took place (Was the reaction faster? Did the car deviate from the expected path?)
2. Why did the effect happen?
3. What is the best that can happen?

1.5 Process mining

To verify the effects of the auditory advisory system, data representing the behavior of the drivers during the experiments need to be analyzed and evaluated. Process mining, i.e extracting valuable, process-related information from the event logs, complements existing approaches to Business Process Management (BPM)[8]. BPM primarily focuses on the analysis to process management and the organization of the work from process automation and process analysis, and aims to improve operational business processes, possibly without the use of new technologies. BPM is often associated with software to manage, control and support operational processes. As BPM heavily relies on process models, process mining plays a very important role in raw data analyzing. Process mining, which instead focuses on the process and uses the actual data, is bridges the gap between classical process model analysis and data oriented analysis like data mining and machine learning. In this case, relating to the driving behavior, data like steering wheel angles, velocities, accelerations, reaction times, longitudinal/lateral position and etc. will contribute to build a model to illustrate how drivers will behave with and without the auditory advisory system in different scenarios. In Chapter 4, data mining will be introduced in detail.

2

Methods

2.1 Overview

The whole process of the thesis work is illustrated in the Figure 2.1

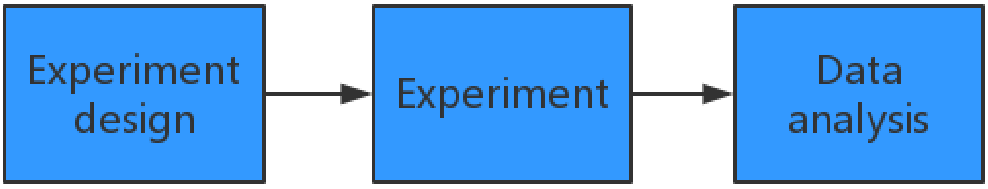


Figure 2.1: The process of the thesis work

During the experimental design all the details of the experiments and the processes need to be verified. Additionally, all desired data, i.e. the data useful for verifying the performance of the 3DATIS, need to be specified. What type of information, how to display the information and how to eliminate the bias also need to be taken into consideration. In terms of data analysis, methods need to be found in order to process the data and conclude results relating to the main research questions defined in the Section 1.4.

2.2 Experiment design

2.2.1 Time to Collision (TTC)

In ADAS, time to collision is a very essential element in vehicles' human machine interface (HMI) design. Time to Collision (TTC) has been verified to be a very effective way to eliminate the severity of the vehicle collision and recognize critical or normal behavior. As illustrated [9] in Figure 2.2.

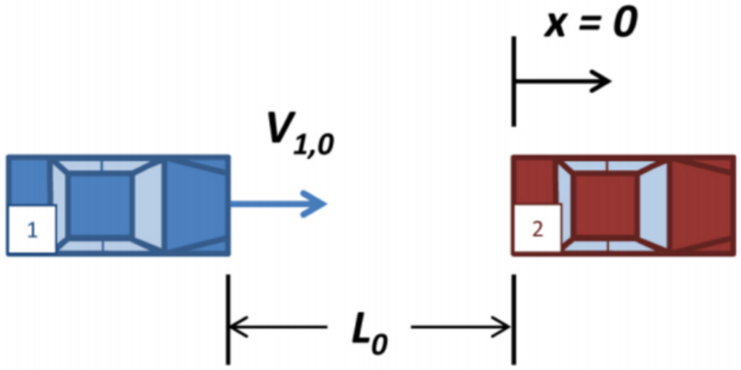


Figure 2.2: The definition of Time to Collision

The definition of TTC is

$$TTC = \frac{L_0}{V_{1,0}}$$

where L_0 is the distance between the back of the front vehicle and the front of the rear vehicle, and $V_{1,0}$ is the difference of the velocities between the two vehicles.

Some studies directly use TTC in the designing of active safety. M.Wang designed an in-vehicle visual advisory system to call attention to aware the other road users' locations and distances.

Figure 2.3: The interface of the visual advisory system

In M.Wang's study, the warning interface was divided into three levels, illustrated in the Figure 2.3. Table 2.1 demonstrates the meaning of the interface.

In Figure 2.3, to the left, is shown the user interface when there are three other road users in close vicinities to the ego vehicle, one to the front right, one to the

Level	TTC	Distance to Collision
Informative(white)	>6s & <9s	<4.5m
Advisory(orange)	3s to 6s	<3.5m
Critical(red)	<3s	<2.5m

Table 2.1: The explanation of M.Wang's ATIS interface design

rear right, and one to the back. The white color signifies that the TTC for all the road users is between 6 and 9 seconds. To the right in Figure 2.3 is shown the user interface when there are two pedestrians, in close vicinity to the ego vehicle, one in front, and one to the rear right in the blind spot. In addition, a road user is very close to the ego vehicle on the immediate right, the red color signifying a TTC of less than 3 seconds.

2.2.2 Design principle

Unlike the visual advisory system, the drivers who use auditory advisory system will get the information passively, rather than observing the interface at regular intervals. That is to say, the drivers themselves cannot control the flow of the information. This behavior of the warning system might leave drivers irritated and annoyed.

Hence, based on the pilot experiments, the informative information feels a bit redundant. Figure 2.4 illustrates how the system will play the alarm to the drivers with respect to TTC

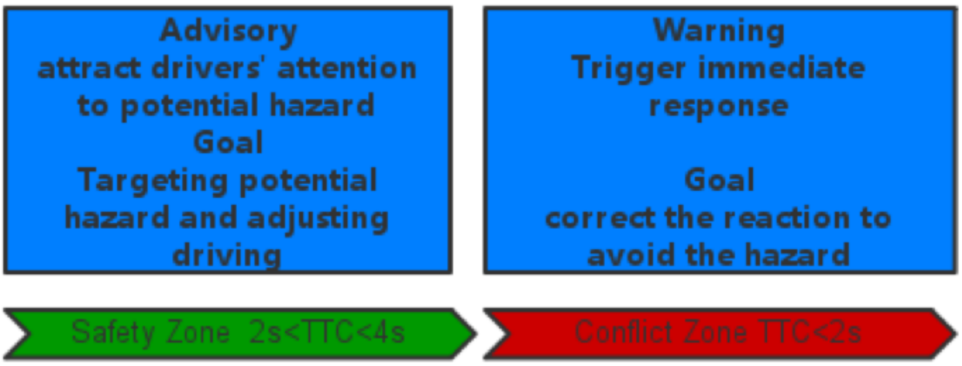


Figure 2.4: The design of the 3DATIS system

As can be seen in Figure 2.4, the threshold of the advisory is shortened between 2 seconds to 4 seconds, according to the decision from the scenario that held before the experiment started, to reduce the mandatory input to the drivers which will cause a "annoy feeling". On the other hand, the warning zone of TTC is set less than 2 second. That is to say, when the event happened, the system will play two different tones with respect to the two situations.

2.2.3 Design of Advisory Traffic Information System (3DATIS)

The simulator room is in the SAFER, Vehicle and Traffic Safety Centre at Chalmers which is located in Lindholmen Science Park. The hardware equipment is shown in Figure 2.5

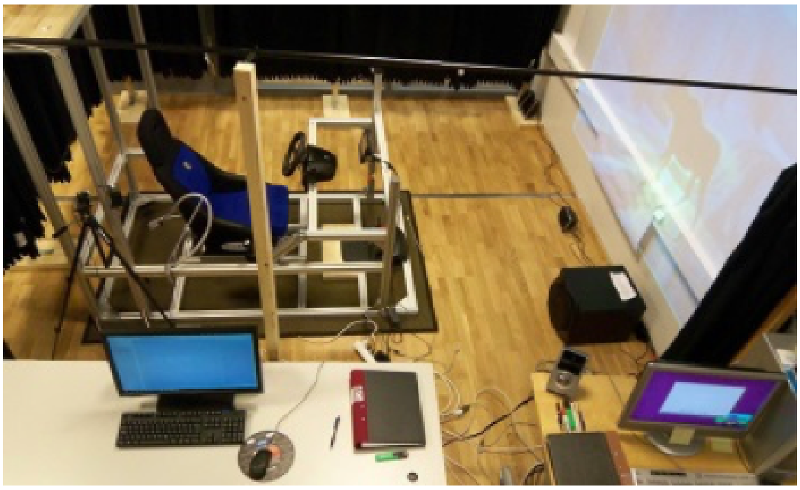


Figure 2.5: The hardware setting

In this experiment, one PC running the STISIM Drive® software which which exports the real-time geographic (coordinates of road users and etc.) and physical (speed, steering wheel angle, acceleration and etc.) data was used driver simulator. A Logitech G25 Racing Wheel, including pedals and a gearbox was installed on the frame. Another PC running MATLAB was used to recieve and process the data obtained from the simulation environment. A 5.1-channel surround-sound system was used to emit the auditory information in the 3DATIS prototype. The arrangement of the loudspeakers and the seating positions of the participants were calibrated according to Dolby 5.1 home theatre speaker guidelines. The speaker system used was a Logitech model Z-5500. Sound-absorbing curtains were installed on three sides of the test area to ensure a good surround effect. A HD projector was used to project the simulated drive scenarios on the front wall. Two webcams were installed to record what the drivers saw on the road, as well as and their reactions to the incidents, e.g. steering, braking. This video data was synchronized with simulation data to better allocate the starting point of the driver reactions with respect to any incident reactions to the incidents.

STISIM

STISIM Drive® is a programmable driving simulator developed by STISIM Drive company in the United States. As the experiment required the driver to operate the vehicle in different traffic situations, an open, programmable, and expandable virtual reality driving simulation software engine is essential. STISIM Drive® provides such a platform and enables researchers to edit the traffic scenarios to fit the requirements.

Pure Data

Pure Data (Pd) is a visual programming language developed by Miller Puckette in the 1990s for creating interactive computer music and multimedia works[7]. In this experiment, the program will play the corresponding pitch and tone. Figure 2.6 illustrates a user interface of PureData. The activation of the different information levels is based on two parameters: safety margin (SM), and TTC.

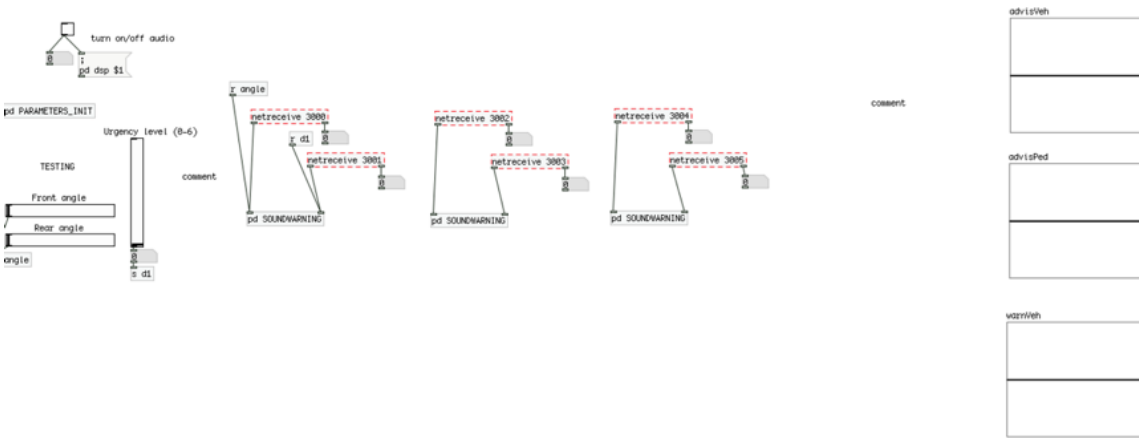


Figure 2.6: The user interface of Pure Data

In this study, the prototype of 3DATIS have been developed with the goal to provide auditory advisory regarding the surrounding environment. The information contains directional risk levels in relation to the participant's own vehicle. The objective is to develop a system capable of letting the driver know where any surrounding object is, and how urgent corrective action is. From the experience during building the system in MATLAB, the expected TTC threshold was too small to handle the situations. Hence, in order to give the participants enough time to react to an emergency situation, the threshold of the TTC was raised to 3 to 6 seconds, and 0 to 3 seconds for the advisory and critical zone respectively. Table 2.1 illustrates the said properties.

Information level	Sound effects	Time to Collision	Distance to Collision
Advisory	Original sound sample	3s to 6s	<3m
Critical	Increased pitch and frequency of looping	<3s	<2m

Table 2.2: Thresholds for warnings in terms of time to collision (seconds) or distance to collision (meters).

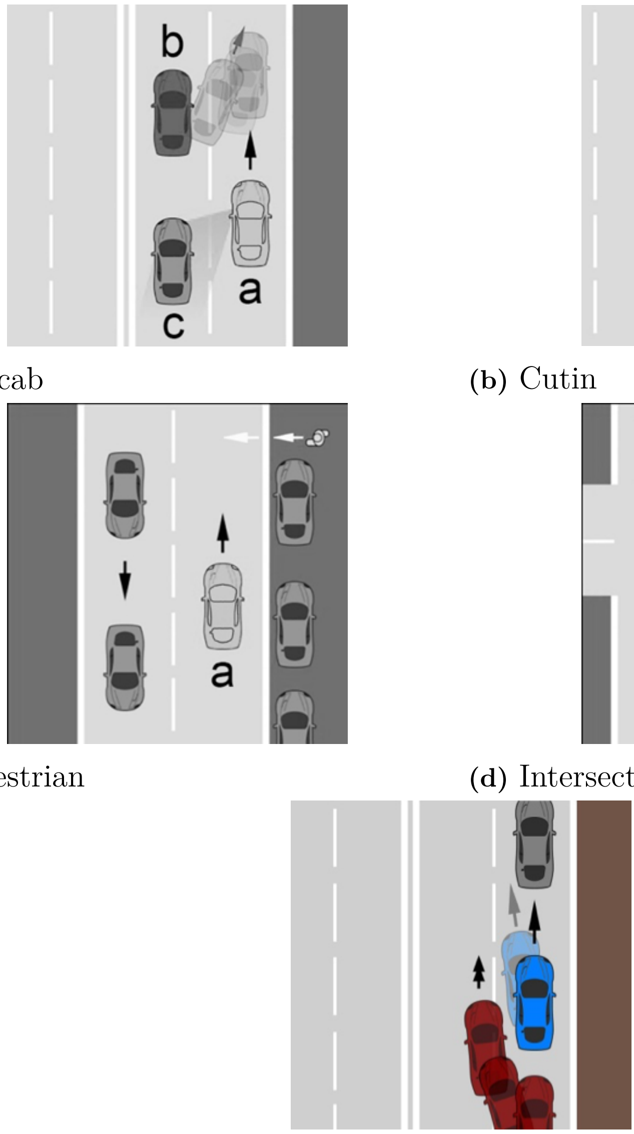
As can be seen in the Table 2.2, distance to collision as another criteria is added. That because if two cars were driving in parallel, the relative speed will be zero and thus TTC can be infinite. In this situation, TTC could not capture the decrease of the distance in lateral position which still might cause the collisions.

The sound effect is another essential part in the 3DATIS design. Hence, choosing a satisfying and a high reliability sound is a critical work. From the beginning, the Swedish automotive OEM's sound sample databases provided several sound samples which had been tested with their global potential customers who gave high acceptances. However, those sounds were initially designed without critical level which is to say, they did not have multi-frequency sound. Hence, a professional acoustic designer from the automotive OEM, designed a hitting-bamboo-like sound which consist of a sharp transient and a short tail. The short transient has many overtones which contributes to it make a multi-frequency sound. The acoustic tail is to decrease the annoyance and give the comfort into the signal similar to the plucking of a string. Hence, this sound has two characteristics which help the drivers in some particular situations: pleasantness and directivity. This sound sample had been tested by several sound experts and research groups to guarantee it was appropriate for the excepted advisory use instead of just alerting.

In this experiment, the 3DATIS prototype was developed in a combination of Pure Data and MATLAB. The Pure Data patch was designed to express the sound effects which related to the auditory information levels as shown in the Table 2.2.

2.2.4 The traffic incident scenarios design

To express the real traffic situation in a good way in the simulator, the research team of M.Wang had observed over 100 naturalistic driving videos. Thus, the scenarios used in this experiment covered common critical situations from those videos.



(a) Redcab **(b)** Cutin

(c) Pedestrian **(d)** Intersection

(e) Overtake

Figure 2.7: Scenarios in the experiment

To represent as many as possible of the situations drivers face every day, two scenarios of the five included pedestrians. On the other hand, three other scenarios were added in order to decrease the learning effects between test drives under different conditions (with and without 3DATIS) and those eight scenarios were randomized for the participants. Five scenarios were going to be studied as illustrated above.

Red cab

In the scenario of Redcab, as illustrated in the Figure 2.7(a), two slow driving vehicles b and c drive in the front and rear position respectively in the left lane. When the ego vehicle approaches car b in a certain distance, car b will suddenly cut into the right lane in front of the participant. In this scenario, the excepted safe reaction from the participants is decelerating to avoid the collision with the front vehicle.

Cutin
Figure 2.7(b) shows car b initially parked at the road shoulder suddenly start moving and cut out to participant's lane and then cut back to the road shoulder. As car c limits participant's driveable region, changing lane for the participants may not be a good choice. The considered safe reaction is to brake or steer slightly to the left.

Pedestrian
In this event, the road is narrowed to include only two lanes. A pedestrian will suddenly walk out from the front of a car parking on the right road shoulder. The pedestrian will not show up until the participants drive really close to the pedestrian, thus, the reaction time will be very short in this scenario. The considered safe reaction in this scenario is to turn the steering wheel quickly as fast as possible.

Intersection
When participants restart the car after stopping before the traffic light, two pedestrians standing oppositely will start to cross the street (they will run the red light) from one side to the other. Furthermore, the pedestrian on the right hand side will be hidden behind the A pillar of the vehicle. In this scenario, the considered safe approach is to brake and wait for the pedestrians to pass by.

Overtaking The car driving in front of the participant will be driving with significantly lower speed, forcing an overtake to occur. While the driver has the attention on the front vehicle, another vehicle will suddenly appear from behind in a very high speed and overtake the participant with a relatively close distance as shown in Figure 2.7(e). The considered safe approach is to turn back to the right lane after overtaking the car b as quick as possible.

2.3 The overall procedure

Before the formal test, the participants need to fill in personal information like age, gender, occupation, the time having driving licence etc. Then, the simulator will be introduced to participants including the steering wheel, the transmission mode, the screen and the pedals. After that, the description of the goal and procedure will be given to the participants, as well as how the 3DATIS works, and the participants are suggested to keep the velocity at 60 kilometers per hour, follow the traffic signs, try to keep themselves in the right lane if there is no need to change the lane and so on. Then, the participants will have a training section on the simulator to be able to adapt the simulator like feeling the feedback of the steering wheel, getting used to the positions of the pedals, and more importantly, to make sure the participants have a correct understanding of the 3DATIS system. When the participants feel properly prepared, the experiment is taken to the next step. In the formal testing, the participants tested twice: once with the advisory from 3DATIS system and once without. To eliminate the bias, both the order of the two tests and all the scenarios which were introduced in Section 2.2.3 are randomized. Furthermore, each test would freeze twice with stopping the program and black screen. When the system was frozen, the participants were required to fill out two situational awareness questionnaires based on situation awareness global assessment techniques (SAGAT) and situation awareness rating techniques[18]. Also, the freeze is randomized.

2.4 Participants' performance measurement

To research how the participants will react to the emergence, it is needed to extract the data from stage to stage from the raw data set. As the researchers would like to know how the 3DATIS influences the drivers' action, there are five important time points needed to be found in the data set, as shown in Figure 2.8 (the *reaction point* and *emergency event start* can change the order as their position depends on their time), so that driving behaviors hided in two groups of data for 30 participants (one with advisory from the 3DATIS and one without) can be researched comparatively. More specifically, for each participant, the behaviors data from advisory voice on to reaction point and reaction point to over take the objective car need to be extracted from the raw data.

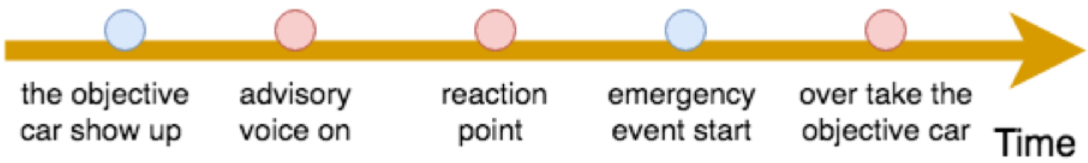
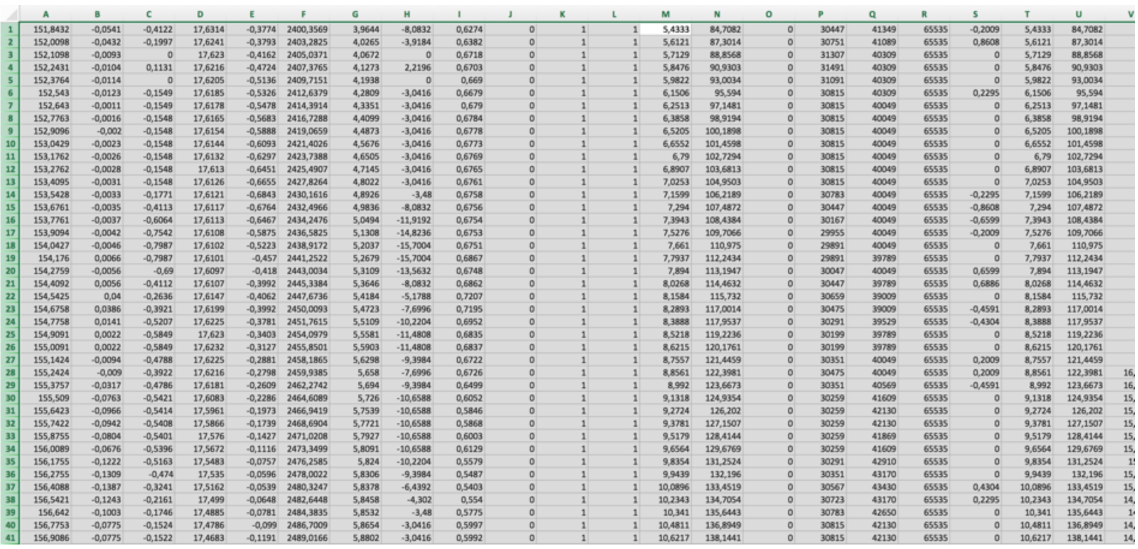


Figure 2.8: Timeline of key points.

Figure 2.9 shows an example of the data set collected from one participant.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	151,8432	-0,0541	-0,4122	17,6314	-0,3774	2400,3569	3,9644	-8,0832	0,6274	0	1	1	5,4333	84,7082	0	30447	41349	65535	-0,2009	5,4333	84,7082	
2	152,0098	-0,0432	-0,1997	17,6241	-0,3793	2403,2825	4,0265	-3,9184	0,6382	0	1	1	5,6121	87,3014	0	30751	41089	65535	0,8608	5,6121	87,3014	
3	152,1098	-0,0093	0	17,623	-0,4162	2405,0371	4,0672	0	0,6718	0	1	1	5,7129	88,8568	0	31307	40309	65535	0	5,7129	88,8568	
4	152,2431	-0,0104	0,1131	17,6216	-0,4724	2407,3765	4,1273	2,2196	0,6703	0	1	1	5,8476	90,9303	0	31491	40309	65535	0	5,8476	90,9303	
5	152,3764	-0,0114	0	17,6205	-0,5136	2409,7151	4,1938	0	0,669	0	1	1	5,9822	93,0034	0	31091	40309	65535	0	5,9822	93,0034	
6	152,543	-0,0123	-0,1549	17,6185	-0,5326	2412,6379	4,2809	-3,0416	0,6679	0	1	1	6,1506	95,594	0	30815	40309	65535	0,2295	6,1506	95,594	
7	152,643	-0,0011	-0,1549	17,6178	-0,5478	2414,3914	4,3351	-3,0416	0,679	0	1	1	6,2513	97,1481	0	30815	40049	65535	0	6,2513	97,1481	
8	152,7763	-0,0016	-0,1548	17,6165	-0,5683	2416,7288	4,4099	-3,0416	0,6784	0	1	1	6,3858	98,9194	0	30815	40049	65535	0	6,3858	98,9194	
9	152,9096	-0,002	-0,1548	17,6154	-0,5888	2419,0659	4,4873	-3,0416	0,6778	0	1	1	6,5205	100,1898	0	30815	40049	65535	0	6,5205	100,1898	
10	153,0429	-0,0023	-0,1548	17,6144	-0,6093	2421,4026	4,5676	-3,0416	0,6773	0	1	1	6,6552	101,4598	0	30815	40049	65535	0	6,6552	101,4598	
11	153,1762	-0,0026	-0,1548	17,6132	-0,6297	2423,7388	4,6505	-3,0416	0,6769	0	1	1	6,79	102,7294	0	30815	40049	65535	0	6,79	102,7294	
12	153,2762	-0,0028	-0,1548	17,613	-0,6451	2425,4907	4,7145	-3,0416	0,6765	0	1	1	6,8907	103,6813	0	30815	40049	65535	0	6,8907	103,6813	
13	153,4095	-0,0031	-0,1548	17,6126	-0,6655	2427,8264	4,8022	-3,0416	0,6761	0	1	1	7,0253	104,9503	0	30815	40049	65535	0	7,0253	104,9503	
14	153,5428	-0,0033	-0,1771	17,6121	-0,6843	2430,1616	4,8926	-3,48	0,6758	0	1	1	7,1599	106,2189	0	30783	40049	65535	-0,2295	7,1599	106,2189	
15	153,6761	-0,0035	-0,4113	17,6117	-0,6764	2432,4966	4,9836	-8,0832	0,6756	0	1	1	7,294	107,4872	0	30447	40049	65535	-0,8608	7,294	107,4872	
16	153,7761	-0,0037	-0,6064	17,6113	-0,6467	2434,2476	5,0494	-11,9192	0,6754	0	1	1	7,3943	108,4384	0	30167	40049	65535	-0,6599	7,3943	108,4384	
17	153,9094	-0,0042	-0,7542	17,6108	-0,5875	2436,5825	5,1308	-14,8236	0,6753	0	1	1	7,5276	109,7066	0	29955	40049	65535	-0,2009	7,5276	109,7066	
18	154,0427	-0,0046	-0,7987	17,6102	-0,5223	2438,9172	5,2037	-15,7004	0,6751	0	1	1	7,661	110,975	0	29891	40049	65535	0	7,661	110,975	
19	154,176	0,0066	-0,7987	17,6101	-0,457	2441,2522	5,2679	-15,7004	0,6867	0	1	1	7,7937	112,2434	0	29891	39789	65535	0	7,7937	112,2434	
20	154,2759	-0,0056	-0,69	17,6097	-0,418	2443,0034	5,3109	-13,5632	0,6748	0	1	1	7,894	113,1947	0	30047	40049	65535	0,6599	7,894	113,1947	
21	154,4092	0,0056	-0,4112	17,6107	-0,3992	2445,3384	5,3646	-8,0832	0,6862	0	1	1	8,0268	114,4632	0	30447	39789	65535	0,6886	8,0268	114,4632	
22	154,5425	0,04	-0,2636	17,6147	-0,4062	2447,6736	5,4184	-5,1788	0,7207	0	1	1	8,1584	115,732	0	30659	39009	65535	0	8,1584	115,732	
23	154,6758	0,0386	-0,3921	17,6199	-0,3992	2450,0093	5,4723	-7,6996	0,7195	0	1	1	8,2893	117,0014	0	30475	39009	65535	-0,4591	8,2893	117,0014	
24	154,7758	0,0141	-0,5207	17,6225	-0,3781	2451,7615	5,5109	-10,2204	0,6952	0	1	1	8,3888	117,9537	0	30291	39529	65535	-0,4304	8,3888	117,9537	
25	154,9091	0,0022	-0,5849	17,623	-0,3403	2454,0979	5,5581	-11,4808	0,6835	0	1	1	8,5218	119,2236	0	30199	39789	65535	0	8,5218	119,2236	
26	155,0091	0,0022	-0,5849	17,6232	-0,3127	2455,8501	5,5903	-11,4808	0,6837	0	1	1	8,6215	120,1761	0	30199	39789	65535	0	8,6215	120,1761	
27	155,1424	-0,0094	-0,4788	17,6225	-0,2881	2458,1865	5,6298	-9,3984	0,6722	0	1	1	8,7557	121,4459	0	30351	40049	65535	0,2009	8,7557	121,4459	
28	155,2424	-0,009	-0,3922	17,6216	-0,2798	2459,9385	5,658	-7,6996	0,6726	0	1	1	8,8561	122,3981	0	30475	40049	65535	0,2009	8,8561	122,3981	16,
29	155,3757	-0,0317	-0,4786	17,6181	-0,2609	2462,2742	5,694	-9,3984	0,6499	0	1	1	8,992	123,6673	0	30351	40569	65535	-0,4591	8,992	123,6673	16,
30	155,509	-0,0763	-0,5421	17,6083	-0,2286	2464,6089	5,726	-10,6588	0,6052	0	1	1	9,1318	124,9354	0	30259	41609	65535	0	9,1318	124,9354	15,
31	155,6423	-0,0966	-0,5414	17,5961	-0,1973	2466,9419	5,7539	-10,6588	0,5846	0	1	1	9,2724	126,202	0	30259	42130	65535	0	9,2724	126,202	15,
32	155,7422	-0,0942	-0,5408	17,5866	-0,1739	2468,6904	5,7721	-10,6588	0,5868	0	1	1	9,3781	127,1507	0	30259	42130	65535	0	9,3781	127,1507	15,
33	155,8755	-0,0804	-0,5401	17,576	-0,1427	2471,0208	5,7927	-10,6588	0,6003	0	1	1	9,5179	128,4144	0	30259	41869	65535	0	9,5179	128,4144	15,
34	156,0089	-0,0676	-0,5396	17,5672	-0,1116	2473,3499	5,8091	-10,6588	0,6129	0	1	1	9,6564	129,6769	0	30259	41609	65535	0	9,6564	129,6769	15,
35	156,1755	-0,1222	-0,5163	17,5483	-0,0757	2476,2585	5,824	-10,2204	0,5579	0	1	1	9,8354	131,2524	0	30291	42910	65535	0	9,8354	131,2524	1
36	156,2755	-0,1309	-0,474	17,535	-0,0596	2478,0022	5,8306	-9,3984	0,5487	0	1	1	9,9439	132,196	0	30351	43170	65535	0	9,9439	132,196	15,
37	156,4088	-0,1387	-0,3241	17,5162	-0,0539	2480,3247	5,8378	-6,4392	0,5403	0	1	1	10,0896	133,4519	0	30567	43430	65535	0,4304	10,0896	133,4519	15,
38	156,5421	-0,1243	-0,2161	17,499	-0,0648	2482,6448	5,8458	-4,302	0,554	0	1	1	10,2343	134,7054	0	30723	43170	65535	0,2295	10,2343	134,7054	14,
39	156,642	-0,1003	-0,1746	17,4885	-0,0781	2484,3835	5,8532	-3,48	0,5775	0	1	1	10,341	135,6443	0	30783	42650	65535	0	10,341	135,6443	1
40	156,7753	-0,0775	-0,1524	17,4786	-0,099	2486,7009	5,8654	-3,0416	0,5997	0	1	1	10,4811	136,8949	0	30815	42130	65535	0	10,4811	136,8949	14,
41	156,9086	-0,0775	-0,1522	17,4683	-0,1191	2489,0166	5,8802	-3,0416	0,5992	0	1	1	10,6217	138,1441	0	30815	42130	65535	0	10,6217	138,1441	14,

Figure 2.9: An example of raw data.

In Figure 2.9, each column has it own meaning. For example, column A holds the absolute time starting from switching on the simulator to the end and the samples taken approximately eight times per seconds. Some important variables that will be used in the data analysis, are shown in Table 2.3: The Column V holds the

Column A	Relative time
Column C	Lateral acceleration
Column E	Velocity
Column F	Absolute distance
Column H	Steering angle
Column I	Gas pedal
Column J	Deceleration
Column K	Times of collisions
Column O	Advisory indicator (0=off; 1=on)
Column V	Longitudinal distance to the road user
Column W	Lateral position to the road user
Column X	Forward speed of the road user

Table 2.3: Thresholds for warnings in Terms of time to collision (seconds) or distance to collision (meters).

value 999 and Column X keeps an certain initial value until the road user appear in the drivers' sight and that point can be the an index of the point *the objective car show up*, and Column W holds the a certain initial value until the road user starts behaving which forces the participants to have to do something to avoid the collisions. And the changing point of Column W is also an index that we divide the process into two basic periods, *before the emergency* and *after the emergency*.

Finding the reaction point is the most essential and complex part in finding these five points. The drivers' behaviors are essentially given by changes in three quantities: Steering wheel angle, acceleration (gas pedal) and deceleration (brake pedal). For example, participant 2's Cutin scenario behavior is illustrated in Figure 2.9. The red curve is the acceleration (increase means hit the gas pedal). The blue curve shows the steering wheel angle (decrease means turning left and increase means turning right). The yellow curve is the brake pedal (negative value when braking). Finally, the purple line as the lateral distance of the car parked in the road shoulder, which starts to move at the time indicated by the green vertical line. We define the valley value of each curve is the action-ending point then move backward to find the peak value as the action-start point. After that, by comparing the three action-start points, we can find the earliest one to be the reaction point. As can be seen in Figure 2.9, since there is no braking (Column J holds only 0's), only the steering wheel and gas pedal need to be compared. Obviously, the action of releasing gas pedal is earlier than the turning the steering wheel. Hence, the reaction point of this scenario is on the point where the red vertical line is, in Figure 2.10.

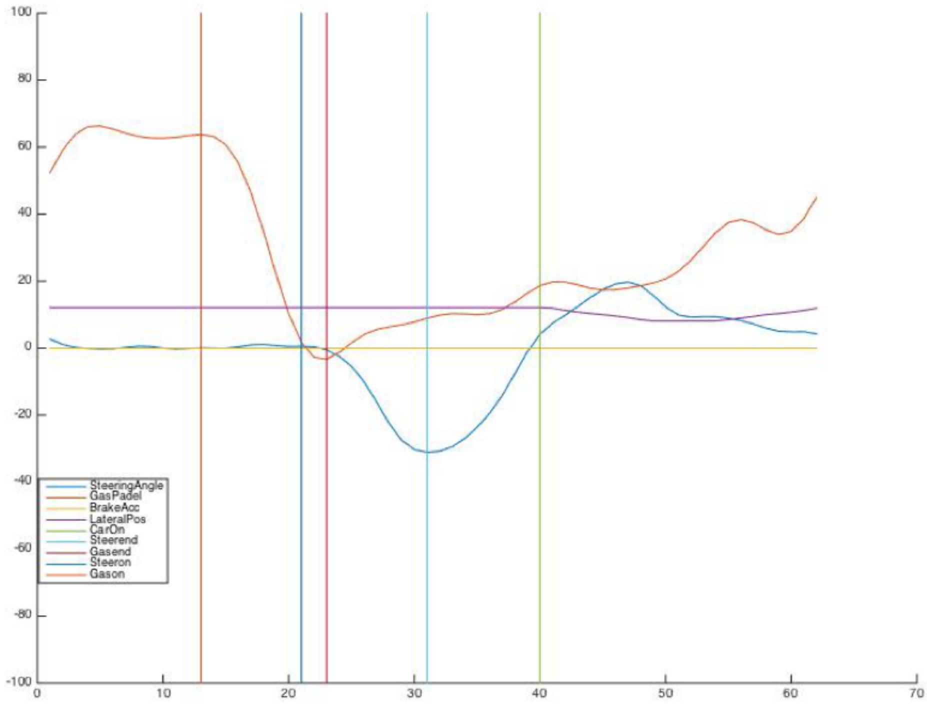


Figure 2.10: An example of the behaviors curves from the collected data.

The precise measurements for each stage of each scenario are as follows:
1.Number of collisions: A direct indicator giving the number of collisions during the driving scenario. Clearly, the objective of the 3DATIS system is to reduce this number.
2. Response time: the TTC at the *reaction point*
3. Steering performance (*degree*):
The Mean Steering wheel angel is the absolute mean value of turning the steering wheel to deal with the event, between the action-start and action-end points. Maximum Steering wheel angle (SA): The relative value between the maximum steering wheel angle and minimum one which shows the range of the steering wheel angle.
4. Gas pedal performance ($feet/second^2$)
Mean acceleration is the absolute mean value of acceleration due to the throttle during the stage.
Maximum acceleration is the difference between maximum and minimum acceleration during the stage. It gives the amplitude of the acceleration.
5. Brake pedal performance ($feet/second^2$)
Mean deceleration is the absolute mean value of deceleration due to the brake pedal. Maximum deceleration is the difference between the maximum and minimum deceleration during the stage and gives the amplitude of the deceleration.
6. Video recording: The behavior of the participants during the experiment were recorded by two cameras which is used to research drivers' behaviors. The video can be matched with the raw data set, used to have a double check with drivers'

reactions point.

After the time when the advisory sound is activated, the additional following measurements are collected:
1. Standard deviation of lateral position (SDLP): how the participants control the car moving horizontally, in order to research the lane-keeping ability of the participants ($feet$).
2. Standard deviation of the speed (SDV): the dispersion of the speed indicates how aggressively the participant controls their vehicle. ($feet/second$)
3. Mean and standard deviation of longitudinal and lateral acceleration. For each measurement, the statistical significance will also be checked. If the *statistical significance* (ρ) is less than 0.05 (5%), it means the compared two groups of data are from the same population [19], as a matter of good scientific practice [20]. In any experiment or observation that involves drawing a sample from a population, there is always the possibility that an observed effect would have occurred due to sampling error alone [21][22].

3
Results

In this chapter, the result of the raw data statistics will be illustrated. In this chapter, only statistically significant results will be discussed. As the data was collected from two groups of experiments (with and without 3DATIS), their significant differences needs to be taken into consideration. Only when two groups have the significant differences, one can consider the data from two experiments are independent and no influence to each other, and in another word, those data are usable for analysing.

3.1 Situational awareness assessment

3.1.1 SAGAT accuracy rate

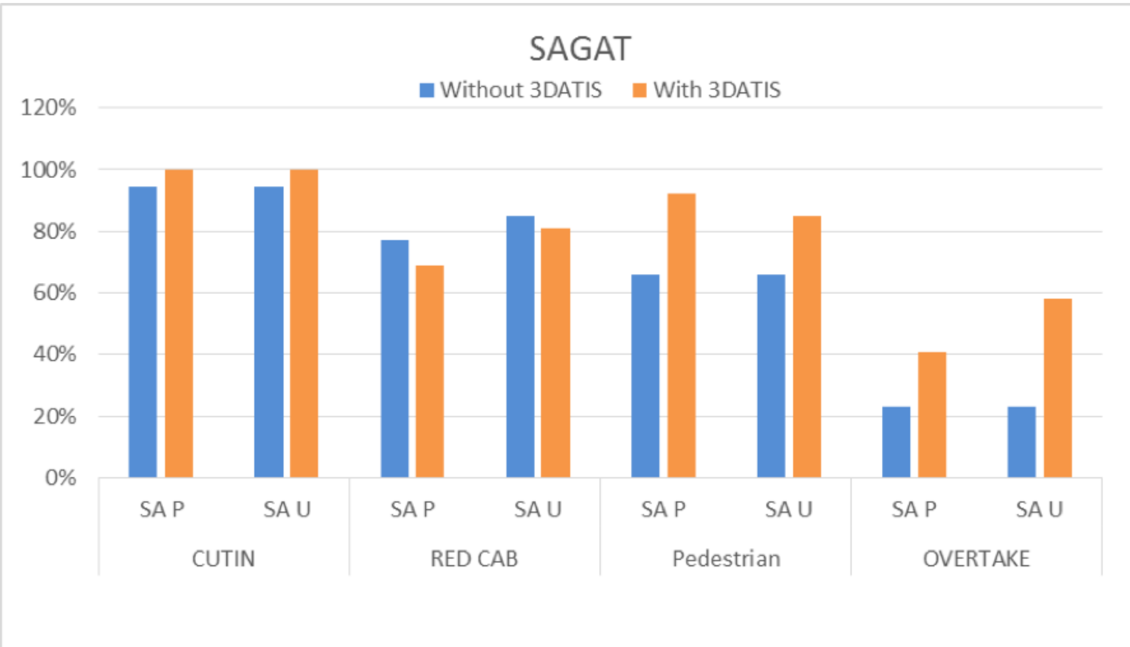


Figure 3.1: Result of the SAGAT accuracy rate.

Situational awareness refers how the drivers aware of the traffic situations before making the decision and SAGAT is to evaluate this respect with a objective test. The results of SAGAT accuracy rate are shown in the Figure 3.1. As SAGAT accuracy rate of scenario *Intersection* did not have the significant difference, only the rest four out of five groups of result have been illustrated. In each scenario, the set 'SA P' means the accuracy that participants know other vehicle's position whereas 'SA U' illustrates the accuracy that participants know how to handle ego vehicle in this situation.

In the *Cutin*, *Pedestrian* and *Overtake* cases, the situational awareness had increased with the helping of 3DATIS, epically for the *Pedestrian* and *Overtake*. Whereas in *Red cab* the things became inverse. According to the interview with the participants, they claimed that in *Red cab*, they could not figure out which road user the indicate sound refereed to, as there were two road user in the almost same direction.

3.1.2 SART score

The situational awareness rate techniques (SART) scores indicates drivers' subjective rating regarding situational awareness in each scenario[18]. The results can be seen in the Table 3.1.

Here UI (user interface) means the tests with 3DATIS, BASE means the tests without 3DATIS. The lower the point, the higher situational awareness the participants thought they get. The questions can be found in the Appendix 1. Here, BASE means without the 3DATIS and UI (user interface) means with the help of 3DATIS

Scenario	SART Question	BASE Mean(STD)	UI Mean(STD)
Pedestrian	1	6.11(0.78)	4.77(1.42)
	2	6.33(0.78)	5.15(1.14)
	3	4(2.24)	4(1.35)

Table 3.1: The result of SART score.

In the *Cutin*, *Intersection*, *Redcab* and *Overtake*, no statistical significance can be found between two groups of tests (the statistical significance indicator $\rho alllargerthan0.05).Ontheoth$

3.2 Drive performance measurement

3.2.1 Number of collisions

The number of collision is a direct indicator to illustrate the benefit that we want to get from 3DATIS system. As illustrated in Figure 3.2, the collision rate was greatly reduced in most cases when driving with the 3DATIS system. Especially for the *Intersection* and *Pedestrian*, the number of collision were halved with the help of 3DATIS. The reason behind this result was that compared to the other scenarios, the pedestrians in *Intersection* and *Pedestrian* initially hidden by the A pillar of the car and a car parking at the road shoulder respectively. As the objects in both scenarios are hidden in some sneaky places, the drivers cannot be aware of the surrounding situation until the advisory voice is triggered or see the objects moving. However, there will be too few seconds left to react when the participants see the objects, and that is why there are big contrasts when it comes to *Intersection* and *Pedestrian*.

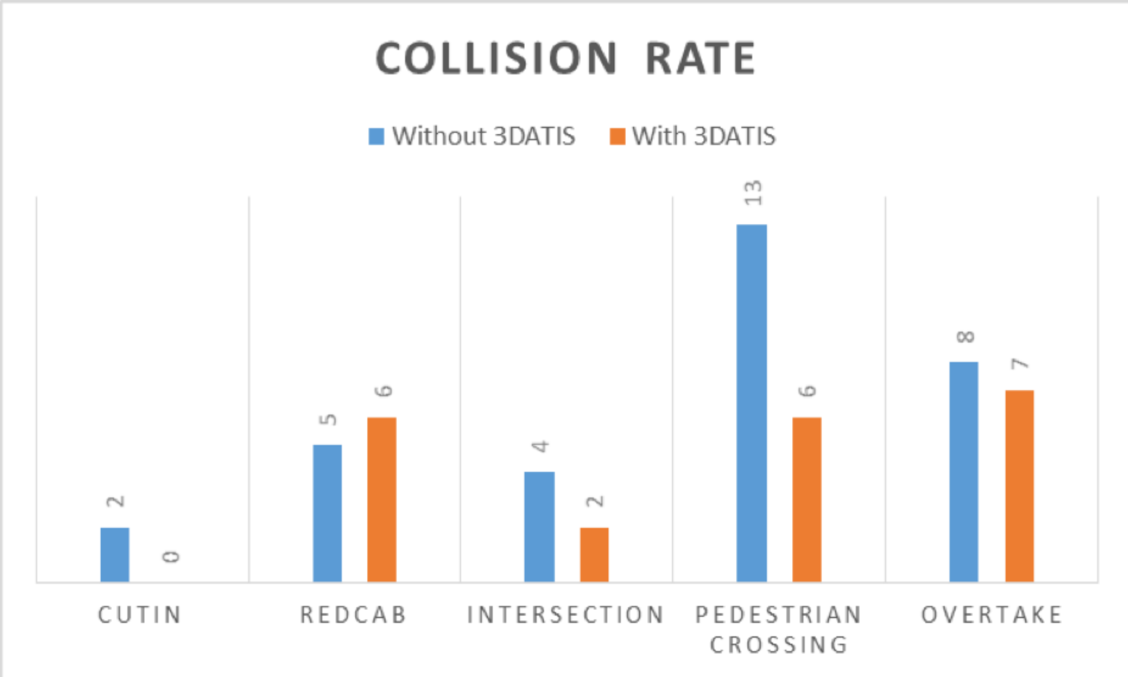


Figure 3.2: The result of collision number.

3.2.2 Drivers' vehicle control inputs in response to each event

Generally speaking, the acceleration represents the participants' reaction to the event and the standard deviations of which express the intensity of the action. The higher the value, the more intense the action. Hence, it reflects the maneuverability of the drivers to the event.

Scenario	Measurements	BASE Mean(STD)	UI Mean(STD)
Cutin	Maximum acceleration	8.53(3.74)	5.59(2.61)
	Mean(acceleration)	0.42(0.15)	0.33(0.11)
Redcab	Maximum acceleration	5.14(2.30)	7.02(2.29)
	Mean(acceleration)	0.34(0.13)	0.48(0.18)
Pedestrian	Maximum acceleration	10.67(7.54)	17.56(9.07)
	Mean(acceleration)	0.73(0.50)	1.11(0.57)
	Maximum steering wheel	24.81(17.07)	51.62(55.23)

Table 3.2: The result of drivers' vehicle control inputs.

As can be seen in Table 3.2, both the maximum values and the mean values decreased in *Cutin*. On the other hand, in *Pedestrian*, the three values illustrated in Table 3.2 were increased. Considering that the number of collisions decreased for both scenarios, the decrease for *Cutin* and the increase for *Pedestrian* were both the right behavior. Because in *Cutin* scenario, the participants would have a preparation when they saw the car parking on the road shoulder (the object), and they would finely adjust the car before the object moves. That means the participants reaction became more accurate and stable. However, in *Pedestrian* they know they need bigger reaction to avoid collision under the help of 3DATIS as the situation was more urgent.

3.2.3 TTC at the reaction point

TTC at the reaction point will decide when and how much time the drivers have left to handle the emergency driving situation. The results are shown in Table 3.3.

Scenario	BASE Mean	BASE STD	UI Mean	UI STD
Cutin	2.27	0.74	3.32	1.75
Redcab	3.43	1.02	6.93	4.74
Intersection	4.01	1.73	6.67	3.29
Pedestrian	3.06	1.41	5.48	2.80
Overtake	0.57	0.56	2.80	1.14

Table 3.3: TTC at the reaction point.

Table 3.3 illustrated that with the help of 3DATIS, the TTC at reaction point of all scenarios got improved approximately two to three second. That is to say, the drivers brought their reaction forward so that they could have two or three seconds more to deal with the emergency.

3.2.4 The result of P1 (from *advisory voice on* to *reachtion point*)

As presented in Section 2.4, the measurements illustrated by scenarios as followed and the significant difference only shown in P1 (from *advisory voice on* to *reaction point*). The abbreviation:
STD: standard deviation
M: mean
Acc: acceleration
Longi:longitudinal
Pos: position
Ang: angle

In *Cutin*, all the three measurements decreased which fits the conclusion from Section 3.2.2, participants' behaviour became more accurate and stable with the help of 3DATIS. However, the standard deviation of steering wheel angle increased. This

Cutin	Measurements	BASE Mean	BASE STD	UI Mean	UI STD
	Lateral_Acc_STD	0.22	0.19	0.08	0.04
	Longi_Acc_STD	0.10	0.12	0.05	0.05
	Steering_Ang_STD	1.17	0.32	0.96	0.37

Table 3.4: P1 of Cutin.

means before the *emergency event start*, participants had already tried to adjust their lateral positions by using steering wheel.

Redcab	Measurements	BASE Mean	BASE STD	UI Mean	UI STD
	Longi_Pos_M	7.39	0.39	7.08	0.45
	Longi_Pos_STD	0.17	0.10	0.11	0.07

Table 3.5: P1 of Redcab.

Intersection	Measurements	BASE Mean	BASE STD	UI Mean	UI STD
	Lateral_Acc_M	0.01	0.02	0.03	0.05
	Lateral_Acc_STD	0.05	0.04	0.10	0.08
	Longi_Acc_M	1.51	1.53	0.72	1.53
	Steering_Ang_STD	0.60	0.23	1.23	0.75

Table 3.6: P1 of Intersection

As can be seen in Table 3.6, the mean and standard deviation of lateral acceleration increased as well as the standard deviation of steering wheel angle. This means the participants were given the awareness when using 3DATIS and they controlled their steering wheel in order to avoid the collisions. On the other hand, the decrease of longitudinal acceleration also shows that they knew they should drive safer in this situation.

3.3 Drivers' subjective feedback to 3DATIS

To measure the overall acceptance and the two sub-measures, usefulness and satisfying, the mean values of nine items on the two acceptance subscales of all participants were calculated. Considering the scale starts at -2, the usefulness ratings are high, especially on item 1,7 and 9. The questionnaire is shown in the Appendix, Questionnaire Part3

Relatively, most scores are neutral or negative which indicate that the auditory information might be irritating during the drive. All rates regarding the satisfaction score are lower than the rating for usefulness. We performed a paired t-test to evaluate the participants' perception on usefulness and satisfaction. The results showed that the usefulness rate was significantly higher than satisfaction.

As shown in Table 3.7, usefulness score was calculated from item 1,3,5,7 and 9, meanwhile satisfying score was calculated from item 2,4,6 and 8.

Item	Number	Mean	STD	χ^2
1. Useful	30	0.97	0.78	24.00
2. Pleasant	30	0.10	0.92	15.00
3. Good	30	0.37	0.93	18.00
4. Nice	30	-0.40	1.04	10.66
5. Effective	30	0.43	0.94	25.66
6. Likable	30	-0.40	0.89	20.00
7. Assisting	30	0.87	0.94	25.00
8. Desirable	30	0.23	1.04	12.33
9. Raising alertness	30	1.13	0.73	33.33
Usefulness	30	0.77	0.77	29.67
Satisfying	30	-0.18	0.91	20.67

Table 3.7: P1 of Intersection

3.4 Discussion

The results of SAGAT questionnaire shows that the 3DATIS system helps the drivers gain awareness of the surrounding environment. Especially for the *Pedestrian* and *Overtake* test cases, the environmental understanding is significantly increased. These two scenarios have a commonality: both of them have a disadvantage to the participant that the objects are all hidden in blind spots so that the participants will not see them until in close range. So the fact is that the systems give the participants understanding of the surrounding environment even though they cannot see the objects. On the other hand, participants' understanding to the *Redcab* decreased. The reason behind this was explained in the Section 3.1.1.

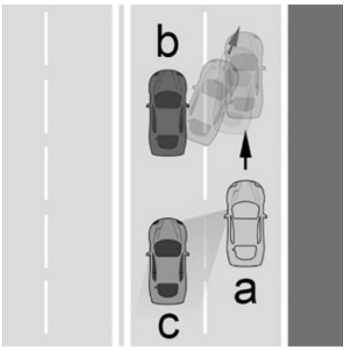
In *Cutin*, with the help of 3DATIS, participants' mean and maximum acceleration shows a decrease tendency which means the action became more accurate and stable. It shows the participants had prepared for the event.

It is interesting to see that in *Redcab*, the participants' performance was opposite to other scenarios. The maximum and mean acceleration at the *reaction point* mentioned in Section 3.2.2 are significantly increased, compared to the BASE. It means the participants were not prepared and performed in a panic. The mechanism behind this is probably that there are two objects in the scenario, and one of them is the disturbance and used to interfere with participants' judgment. It resulted in that when the voice was triggered, the participants could not distinguish which object is the voice referred to and thus causing the drop in driver performance.

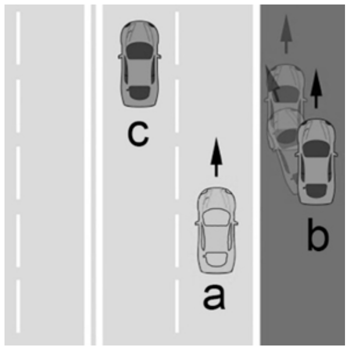
In *Intersection*, besides the TTC at the reaction point, there is no obvious difference can be detected from the measurements. That is to say, except that participant would behave earlier, the reactions including turning the steering wheel, releasing the gas pedal and brake performance were more or less the same. It is also interesting to notice that although the object of *Cutin* and *Intersection* behave in a similar way, i.e. both of them are suddenly moving from right side to the left side, participants reacted differently for the two cases. Drivers were more prone to decelerate in the *Intersection*, whereas in the *Cutin* the participants more often bypassed the obstacles. As Swedish drivers are used to stopping for pedestrians crossing the road, the result might be different for drivers from other parts of the world, where stopping for pedestrians is not so common.

In *Pedestrian*, the road narrowed down to a single lane and the object (a pedestrian) walks unexpectedly from behind a car parked at the right side of the road. Hence, the participants cannot see the object beforehand, unlike the other scenarios. Therefore, in this particular case, participants need to quickly release the gas pedal and turn the steering wheel to avoid collision, which means that if the standard deviations of these quantities is large, the indicates a "good" reaction. When double checking the video recorded from the live experiments, it is also noticed that without the aid of the 3DATIS, a significant proportion of the participants fully applies the brakes when seeing the pedestrian[18], indicating that the drivers were uninformed of the presence of the obstacle.

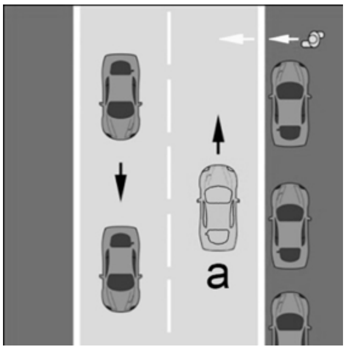
In *Overtake*, the obstacle approaches from the rear at a relatively high speed of 100 km/h[18]. Hence, the advisory sound would directly trigger at warning level (as it is decided by TTC) and therefore there would be only approximately two seconds left for the participant to take action to avoid the collision. From the observation of the videos, we noticed that when the advisory voice was triggered, most participants started to regulate the steering wheel or the gas pedal immediately.



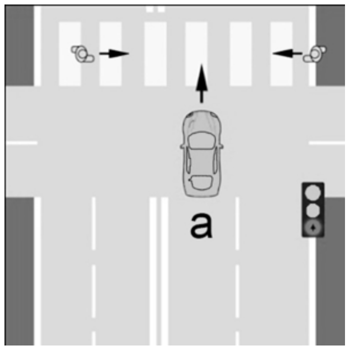
(a) Redcab



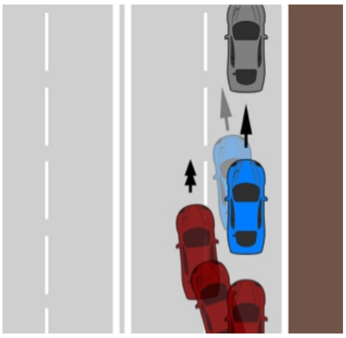
(b) Cutin



(c) Pedestrian



(d) Intersection



(e) Overtake

Figure 3.3: Scenarios in the experiment

4

Process mining

When talking about the data, one can always ask four questions in any situations:

1. What happened? e.g. The ego vehicle deviate from the designed path.
2. Why did it happen?e.g. Why people deviate from the designed path?
3. What will happen? i.e. What can we learn from historic information to make predictions about what is happening at this point.
4. What is the best that can happen? i.e. We want to use analytics to recommend certain things that'll improve the situation.

In Chapter 3, we explained "What happened?" and "Why did it happen?", but still, we cannot directly answer the third and fourth question. Hence, we need to find a special way to analyse those data to get answers. Thinking that all the behaviors to the emergency, including turning the steering wheel, hitting the brake pedal, releasing the gas pedal etc. are actually a continuous process, if we can find a way to build the process model, maybe we can answer the last two questions.

Wil M.P. van der Aalst [8] introduced an algorithm to discover the process model in Petri Net. Verwer et al. [10] introduced a timed syntactic pattern recognition to solve the limitation that Real-time automata has never actually been applied to real data. Salehi et al. [11] created a machine-learning algorithm to identify a car and its driver from detailed driving data.

From the reference above, one can make a prototype in the mind, a discrete event model related to drivers' behaviors and time may be built by *mining* the raw driving data. Hence, we will try to use the process mining methods to analyse driving behaviors.

To verify the effects of the auditory advisory system, data with respect to the driver behaviors collected from the experiments need to be analyzed and evaluated. Process mining, i.e, extracting valuable, process-related information from the event logs, complements existing approaches to Business Process Management (BPM) [8]. BPM primarily focuses on the analysis of process management and the organization of the work from process automation and process analysis, and aims to improve operational business processes, possibly without the use of new technologies. On the other hand, BPM is often associated with software to manage, control and support operational processes. As BPM heavily relies on process models, process mining plays a very important role in raw data analyzing. Process mining focuses on the process but utilizes the actual data, are bridges the gap between classical process model analysis and date oriented analysis like data mining and machine learning.

In this case, related to the driving behavior, data like steering wheel angles, velocities, accelerations, reaction times, longitudinal/lateral position, will contribute to build a model to illustrate how drivers behave with and without the auditory advisory system in different scenarios.

Process mining is a relatively new research discipline that sits between machine learning and data mining on the one hand and process modeling and analysis on the other hand [11]. The idea of process mining is to discover, monitor and improve real processes (i.e not assumed processes) by extracting knowledge from event logs readily available in today's systems [11]. Hence, we can consider the process mining as a "super glue" between data and process as well as the fusion between business decision makers and IT people.

Figure 4.1 gives an overview in a sense. It illustrates that process mining connects BPM and classical data in this pattern.

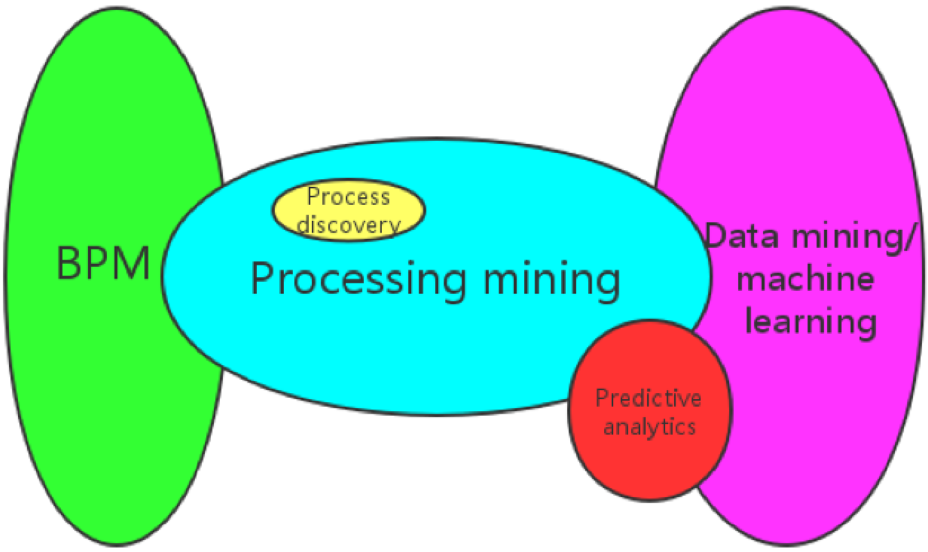


Figure 4.1: The relationship connecting with data mining and BPM.

Figure 4.1 illustrates that process mining establishes links between the actual processes and their data on the one hand and process models on the other hand. As shown in Figure 4.2, the "World" represent the different types of raw data. Most information systems store information in unstructured form. For example, raw data is sometimes scattered over many tables. In such cases, event data exist but some efforts are needed to extract them.Thus by using a software system (in a company, it can be provided by the IT department according to the requirements from the data analysts), the event log which records the necessary information in some specific format can be gotten. Then, by using some algorithm (here we will use *Alpha-algorithm* [8]), the process model can be discovered to analyse the "World", i.e to answer the questions illustrated at the beginning of this chapter.

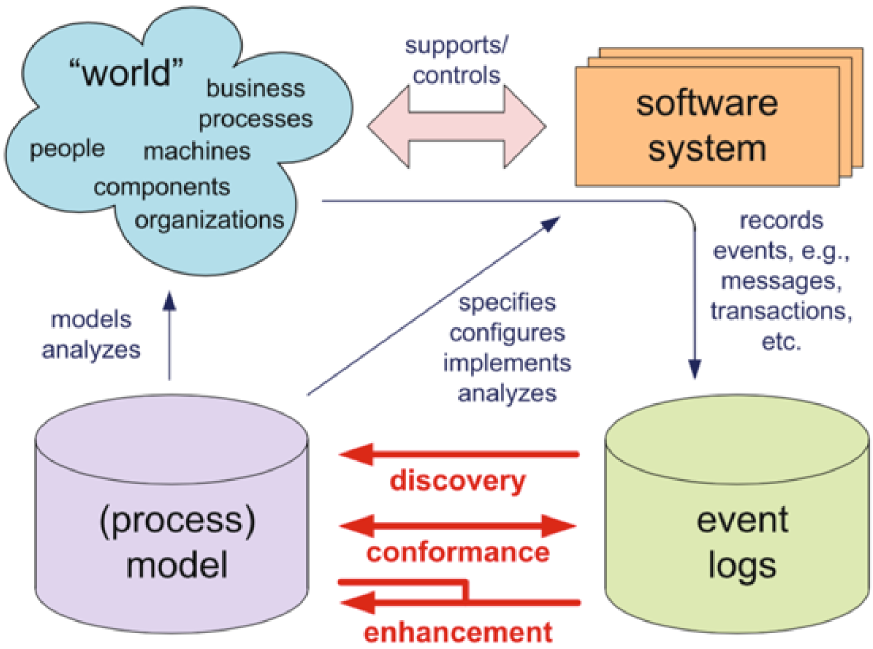


Figure 4.2: The steps and relationships in process mining. [8]

4.1 From raw data to event logs

After finishing the experiment, the raw data set includes all information from the simulator including the time, velocity, steering angle, brake pedal, gas pedal, acceleration, distances to road users, TTC to the road users, road users' speed and etc.. Those data exist in the columns of the raw data set. How can we extract the event logs from the raw data to fit the requirements of discovering the process model?

For the row data, we have three main columns of data need to be extracted i.e.the data from the steering angle, gas pedal and brake pedal. We need to compare the order of each reaction in the data stream, as there can be not just one action for each stream. However, to transform the row data to the event log will become sophisticated because there are much noises in the columns. There are many reasons that can cause those shakes or tingles, like muscle control and driving habits. Hence, we can consider these "useless behaviors" as noise superimposed on the "right behaviors". The task is thus to separate the noise from the actual driver behavior.

The spectral subtraction method [24] is a simple and effective method for noise reduction. As the noisy is uncorrelated, and there are no connection with any occurring incident, the spectral subtraction will be a good choice to remove the noise from the non-noisy signal.

We will not introduce the specific theory of spectral subtraction in this thesis, if you are interested in spectral subtraction, you can go to `http://dsp-book.narod.ru/304.pdf` to have a check, and the code in Matlab is also illustrated as following. One example of spectral subtraction from the real test is shown as in Figure 4.3

```
function [P_gas] = spectral_subtraction(gas)
y = gas;
N_gas = length(y);          % the length of the frame
max_gas = max(y);

%add Gauss noise
noise_estimated = random('norm', 0, 0.1*max_gas, [N,1]);
fft_gas = fft(y);
fft_gas = fft(noise_estimated);
E_noisegas = sum(abs(fft_gas)) / N_gas;
mag_gas = abs(fft_gas);
phase_gas = angle(fft_gas);   % Keep the phase infomration
mag_g = mag_gas - E_noisegas;
mag_g(mag_g<0)=0;

% restore
fft_gas = mag_g .* exp(1i.*phase_gas);
g = ifft(fft_gas);
P_gas = real(g);
end
```

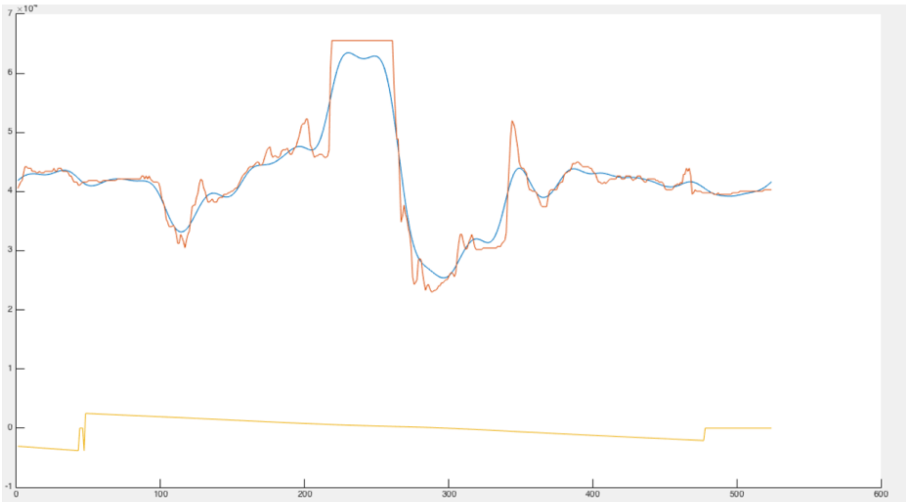


Figure 4.3: The original data stream(red) and spectral subtraction result(blue).

In Figure 4.3, the red curve is a plot from the raw steering angle data. As can be seen, there is much noise in the data, making it hard to to distinguish the behavior from it. After applying the spectral subtraction, as illustrated in the blue curve in the Figure 4.3, the noise is filtered out and the curve becomes smoother. Therefore, general behaviors can more easily be recognized. As Figure 4.4 shows, the behaviors are as follows:: 1. Turn left, 2. Turn right, 3. Turn left, 4. Turn right. Other reactions, such as the usage of accelerator and brake pedals, can also be discovered in a similar fashion. Then, comparing the time when each reaction happen, a sequence of behavior can be found, an example is shown in Figure 4.5.

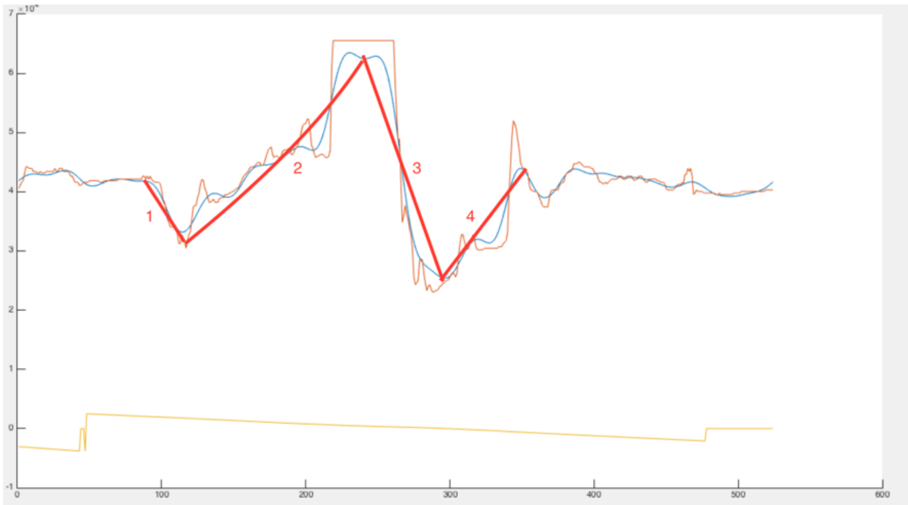


Figure 4.4: The trend of steering wheel angle.

4.2 Event logs

Figure 4.5 shows a standard event log sheet used in process mining. Furthermore, the event logs shown in Figure 4.5 are generated using data collected from the driving experiments. This figure shows that there are three fundamental variables, as can be seen by the respective columns.

4.2.1 An example of the event log

1	Case ID	Start Timestamp	Complete Timestamp	Activity
2	Person 1	31/01/2016 00:03:18.703	31/01/2016 00:03:20.603	Gas off
3	Person 1	31/01/2016 00:03:19.336	31/01/2016 00:03:20.603	Turn left
4	Person 1	31/01/2016 00:03:20.603	31/01/2016 00:03:21.237	Turn right
5	Person 1	31/01/2016 00:03:20.837	31/01/2016 00:03:23.571	Accelerate
6	Person 2	01/02/2016 00:00:00.000	01/02/2016 00:00:00.625	Gas off
7	Person 2	01/02/2016 00:00:00.750	01/02/2016 00:00:02.500	Brake
8	Person 2	01/02/2016 00:00:01.250	01/02/2016 00:00:01.625	Turn left
9	Person 2	01/02/2016 00:00:01.625	01/02/2016 00:00:02.000	Turn right
10	Person 2	01/02/2016 00:00:02.000	01/02/2016 00:00:02.375	Turn left
11	Person 2	01/02/2016 00:00:01.875	01/02/2016 00:00:03.000	Accelerate
12	Person 3	02/02/2016 00:02:51.152	02/02/2016 00:02:54.151	Gas off
13	Person 3	02/02/2016 00:03:01.183	02/02/2016 00:03:03.282	Accelerate
14	Person 3	02/02/2016 00:03:00.783	02/02/2016 00:03:01.316	Turn left
15	Person 3	02/02/2016 00:03:01.416	02/02/2016 00:03:02.182	Turn right
16	Person 3	02/02/2016 00:03:02.183	02/02/2016 00:03:04.182	Turn left
17	Person 4	03/02/2016 00:02:59.220	03/02/2016 00:03:01.416	Gas off
18	Person 4	03/02/2016 00:03:00.720	03/02/2016 00:03:01.353	Turn left
19	Person 4	03/02/2016 00:03:01.453	03/02/2016 00:03:02.086	Turn right
20	Person 4	03/02/2016 00:03:02.087	03/02/2016 00:03:03.119	Turn left

Figure 4.5: An example of the event log of *Cutin*.

In Figure 4.5, a single row does not mean a complete process instance, just an event. Since a data set used in process mining consists several events, these data are often referred to as an event log. In an event log:

- Each event reflects to a behavior that was implemented in the whole process.
- Multiple events are linked together in a process instance or case.
- Logically, each case forms a sequence of events—ordered by their timestamp[8].

As seen in the Figure 4.5, one case ID is constructed by a complete series of handling behaviors during the scenario *Cutin*. Thus, the number of the drivers can be the case ID. There are several activities occurring for each case and each of them corresponds to a driving behavior.

- Gas off: releasing the gas pedal.
- Accelerate: hitting the gas pedal.
- Brake: hitting the brake pedal.
- Turn left: turning the steering wheel left.
- Turn right: turning the steering angle right.

• Event on: The road users move the car/start to cross the road suddenly.

The activities above are assumed reasonable for the process mining. Furthermore, the *time-stamps* columns show the handling time of each action clearly. The timestamps give additional information when investigating the driver behavior patterns. For example, by comparing the mean value of each action's time and frequency, the statistically most likely driving behavior, based on the choices of all participants, can be determined for each scenario.

From the data sample in Figure 4.5, we can see why even doing simple process related analyses, for example count the frequency of each behaviors, or the time between activities, is no way to use standard tools such as Excel. Process instances are scattered over multiple rows in a spreadsheet and can only be linked by adopting a process-oriented meta model. For example, if we look at the rows 6-11 in Figure 4.5, you can see one process(Person 2) that starts with the status Registered on 1st February 2016, 00:00 (a relative value), moves on to 00:00:03 where we can see the complete action last for three seconds.

There are three types of process mining that can use event logs as illustrated in the Figure 4.2, *discovery*, *conformance*, *enhancement*. The first one is *discovery*. The discovery technique which we will use in this thesis takes an event log and thus creates the process model without using any other types of data. An example is the *Alpha-algorithm*[13] which will be introduced in the coming sections. This algorithm uses the event log to create a Petri net to describe the behavior. For example, by using the *Alpha-algorithm*, the Petri net can be directly built without using redundant information.

4.2.2 Case ID

A case ID is a defined instance of an action/process. The precise meaning of a case depends on in which stage in the process the case is found. For example:

• In a hospital, booking a doctor is one case.
• In a purchasing process, the case could be the writing of a purchase order.
• In a police station, recording reporters' information would be a case

For every event/activity, one need to identify which case it belongs to so that the process mining algorithm can distinguish between the different executions.

The case ID can determine the scope of the process and where the process starts and ends respectively. In fact, the case ID can be constructed in more than one way. An example could be the following:

If professors from Division of Systems and Control would like to buy some stuff in their offices, like printers, computers or some new chairs and etc., then the purchasing process can be set up in two approaches:

1. One can regard the processes of a specific lead through the purchasing funnel as the process you would like to analyze. Thus the product lead number will be the case ID. E.g. computer 1, chair 2 and etc..
2. On the other hand, one can consider the whole purchasing process for a professor as the process scope and thus, professors' names can be the case ID.

The two alternatives are all logical and reasonable based on the goal of purchasing appliances and what kind of reault that people want to get from the data.

Rule #1: The case ID determines the scope of the process[17].

4.2.3 Activity

An activity constructs one step in the process. For example, if a professor wants to buy a new computer for his office, then the process may contain the following activities: Writing report, Sending to the secretary, Approved by the financial department, Request rework, Ordering from the shop, Refuse etc.. Some of the activities might be executed more than once. For instance in the example above, the action "Writing report" might be executed every time when "Request rework" occurred.

All the activities in the process or the different procedures should be named. If one has only one activity for each case, then the event log is not specific enough. The events can also include outlier actions not only just the information that attracts people. Of course, it is also necessary to "clean" those outliers before the analysis to access a relatively better conclusion.

Rule #2: The activity name determines the level of detail for the process steps[17].

4.2.4 Timestamp

The third mandatory data is the timestamp which displays the time when each activity occurs. It is essential for both building the sequence for the activities and investigating the timing characters of each case. It is all right to just have a *start time*, however, if an event log also includes a *complete time* column, like illustrates in Figure 4.5, the time of each activity period can be found. This is also called execution time or activity handling time[17]. The activity period helps one to divide the inactive waiting time from the active one and this is one of the advantages, compared to having only a start time column.

Rule #3: If you don't have a sequentialized log file, you need timestamps to determine the order of the activities in your process[17].

4.2.5 Other variables

Additional variables can also be added in the event log to analyze other characteristics or properties of the process. The suitable additional variables depend on the domain of the process. As this thesis will not use other variables to analyse the behavior of the drivers, additional attributes will not be introduced. Please see [17] for more detail on this.

4.3 Petri net

As Petri nets are foundational process notation and oldest and best investigated process modeling language, this thesis will use the Petri net to represent the process model. Even if the graphical notation is simple, there are still many analysis techniques that can be used to analyze the Petri nets[**?**][15][16]. A Petri net describes an "action flow", and consists of *places* and *transitions*. The network structure is constant, however, supervised by the firing rule, *tokens* can flow through the "process stream". The state of a Petri net is determined by the distribution of tokens over the places.

Definition (Petri net): A *Petri net* $N = (P, T, F)$ where P is a finite set of *places*, T is a finite set of *transitions* such that $P \cap T = 0$, and $F \subseteq (P \times T) \cup (T \times P)$is a set of directed arcs, called the *flow relation*. A *marked* Petri net is a pair (N, M), where $N = (P, T, F)$ is a Petri net and where $M \in \mathbb{B}(P)$ is a *multi-set* over P denoting the *marking* of the net. The set of all marked Petri nets is denoted $\mathcal{N}$.

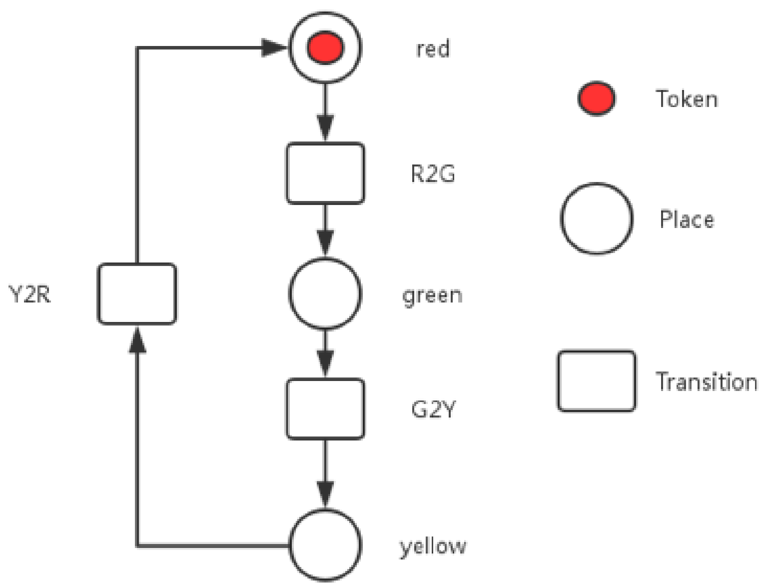


Figure 4.6: An example of Petri net, traffic light.

Here we will use an elementary example to illustrate the Petri nets. A traffic light is a very simple process consisting of three states which is obviously the red, yellow and green light, as shown in Figure 4.6.

The process model for the traffic light has the states red, green and yellow as well as the transitions to shift from one state to another. Here we can see the Petri net is static which means that the process is fully described and the net will not be subject to change. However in the Petri nets there are so called tokens, of which there can be several. The tokens can move from one place to another place. In this case, when the transition R2G fires, the token will be moved from the state red to the state green. Then, the transition G2Y can fire moving the token from green to yellow. Finally, the token will be moved from the yellow to the red as a result of firing Y2R.

4.4 Process discovery: Alpha-algorithm

Process discovery is the main job of the process mining task. From an event log, a process model can be built , capturing the behaviors found in the event logs. This section will describe the method mentioned in the previous section, i.e. the alpha-algorithm.

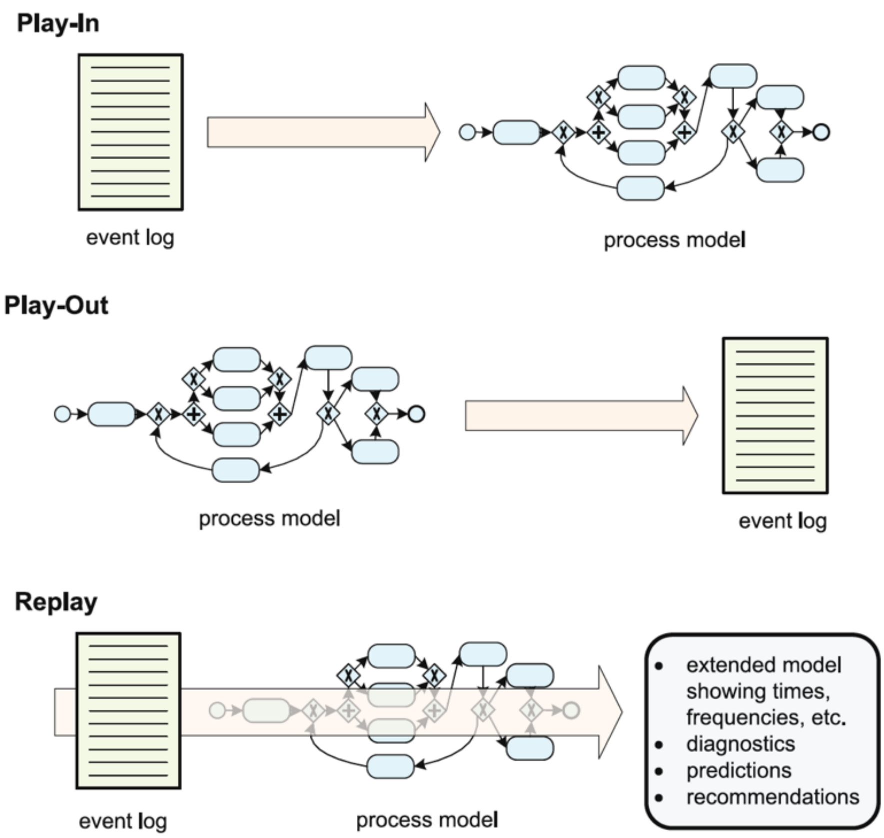


Figure 4.7: A sketch map explaining *Play-in*, *Play-out* and *Replay.* Picture from [8].

One of the most essential elements of process mining is to build a strong connection between a process model and extracting the "reality" from an event log [8], according to Van der Aalst et al. [8], *to Play-in, Play-out, and Replay.* The process discovery corresponds to the Play-in. For Play-in, opposite to the Play-out, the actions behind the event logs will be regarded as inputs and the aim of which is to build a model. The alpha-algorithm is such an example of Play-in technique.

Definition (Process discovery):A *process discovery algorithm* is a function that maps an event log onto a process model such that the model is "representative" for the behavior seen in the event log[8]. The key step is to find such a model.

4.4.1 From an example to access to Alpha-algorithm

As a function, we know that there should be input and output of the Alpha-algorithm. We know that the output of the alpha-algorithm is the process model(it can be a Petri net, BPMN model etc.), so what kind of input does the Alpha-algorithm use? When we apply the Alpha-algorithm and we just focus on control flow like the Activity column in the Figure 5.4, we ignore the resources and other data elements, as well as the actual timestamps of the events taking place. The ordering is the only thing that need to be taken into consideration. Hence, we can convert such an event log to a multiset of traces (because the same trace can appear more than one time) and for each trace there is a sequence of the names corresponding to the activities. Here is an abstract example:

$$L_1 = [< a, b, c, d >^3, < a, c, b, d >^2, < a, e, d >]$$

Here, we can see the log L_1 contains six traces (the index on the right corner mean the number of each order) and they can be considered as six different cases. They are modeled as a sequence of activity names. So the sequence a, b, c, d were executed three times (there are three traces of that type).

The goal of the alpha-algorithm is to capture L_1 to a process model automatically, no matter what kind of way to represent it e.g. BPMN, Petri Net etc.. Here, we will start the Alpha-algorithm with the ordering relations without considering the frequency or some other attributes. In this case, we are only interested in finding in the log.

As we can see in L_1, the sequence $< a, b, c, d >^3$ represents that the event/behavior a is followed by b, b is followed by c and c is followed by d. This relationship is called direct succession. The relations between the event are listed as followed:

• Direct succession: $x > y$, iff for some case x is directly followed by y, thus for L_1, the following relationships can be given:

$$a > b$$

$$a > c$$

$$a > e$$

$$b > c$$

$$b > d$$

$$c > b$$

$$c > d$$

$$e > d$$

• Causality: $x \to y$, iff $x > y$ and not $y > x$. Hence we can get the following relations:

$$a \to b$$

$$a \rightarrow c$$
$$a \rightarrow e$$
$$b \rightarrow d$$
$$c \rightarrow d$$
$$e \rightarrow d$$

• Parallel: $x||y$, iff $x > y$ and $y > x$. In this case, the direct succession relation holds in both directions:

$$b||c$$
$$c||b$$

• Choice: $x\#y$, iff not $x > y$ and not $y > x$, which means x is never followed by y and vice versa:

$$b\#e$$
$$e\#b$$
$$c\#e$$
$$a\#d$$

The relations mentioned above are used to learn patterns in the process. For example, if we see a is followed by b but b is never followed by a, Figure 4.8 can be used to model this behavior.

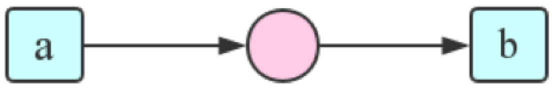


Figure 4.8: Causality patten: $a \rightarrow b$.

If we find that a is sometimes followed by b, but never the other way around and at the same time, a is sometimes followed by c, but c is never followed by a, and b and c never followed one another, we can learn the XOR-split pattern as followed.

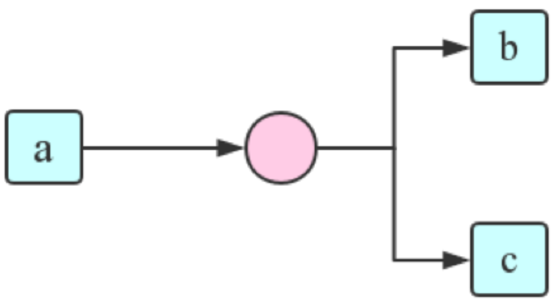


Figure 4.9: XOR-joint pattern: $a \rightarrow b$, $a \rightarrow c$, and $b\#c$.

The corresponding part to the XOR-split is the XOR-join illustrated as follows:

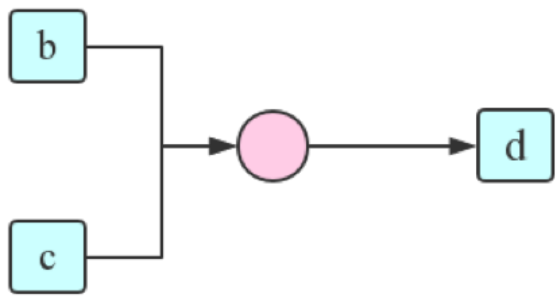


Figure 4.10: XOR-split pattern: $b \rightarrow d$, $c \rightarrow d$, and $b\#c$.

If we look at the concurrency, a is followed by b and c but b and c are never followed by a, we can learn an AND-split pattern:

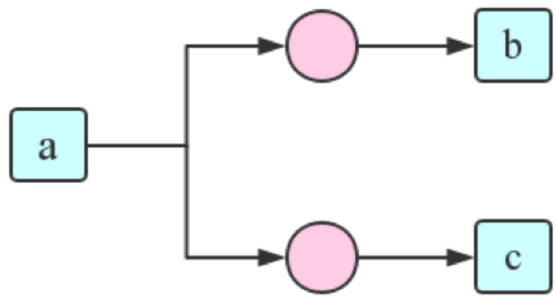


Figure 4.11: AND-split pattern: $a \rightarrow b$, $a \rightarrow c$, and $b||c$.

And the corresponding AND-join pattern:

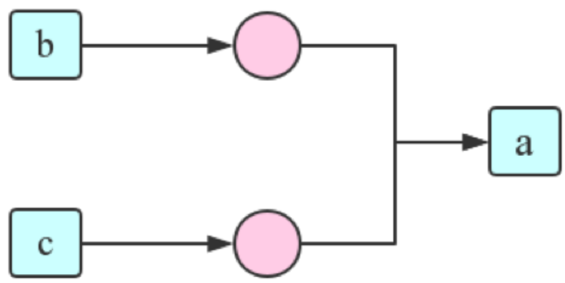


Figure 4.12: AND-join pattern: $b \rightarrow a$, $c \rightarrow a$, and $b||c$.

Hence, based on these patterns, a Petri net can be automatically constructed from Table 4.1 as in Figure 4.13:

$a > b$ $a > c$ $a > e$ $b > c$ $b > d$ $c > b$ $c > d$ $e > d$	$a \rightarrow b$ $a \rightarrow c$ $a \rightarrow e$ $b \rightarrow d$ $c \rightarrow d$ $e \rightarrow d$	$b \| \| c$ $c \| \| b$	$b\#e$ $e\#b$ $c\#e$ $a\#d$

Table 4.1: The relationships extracted from L_1.

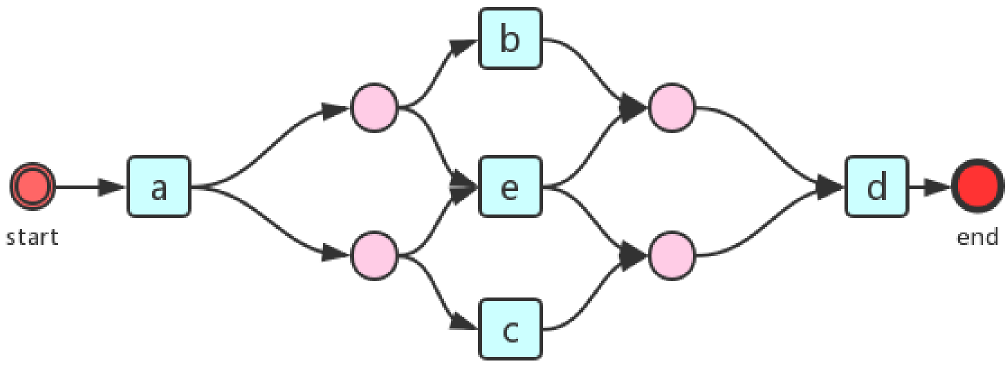


Figure 4.13: The result produced by the Alpha-algorithm from L_1.

This example shows the basic idea of how can we transfer the event log to the process model. However, in this case, it is actually already a bit more involved and furthermore, the Alpha-algorithm can handle more situations.

Here, let us look at L_1 in more detail. When we take an event log, we can talk about so-called footprints and Table 4.2 illustrates them. Table 4.2 illustrates the relation between each sequence displayed by Footprint.

4.4.2 Algorithm

After the basic idea has shown, the Alpha-algorithm can be described as following[23]:
Definition (Alpha-algorithm):

1. $T_L = \{t \in T \mid \exists_{\sigma \in L} \in \sigma\}$

	a	b	c	d	e
a	$\#L_1$	$\rightarrow L_1$	$\rightarrow L_1$	$\#L_1$	$\#L_1$
b	$\leftarrow L_1$	$\#L_1$	$\|\|L_1$	$\rightarrow L_1$	$\#L_1$
c	$\leftarrow L_1$	$\|\|L_1$	$\#L_1$	$\rightarrow L_1$	$\#L_1$
d	$\#L_1$	$\leftarrow L_1$	$\leftarrow L_1$	$\#L_1$	$\leftarrow L_1$
e	$\leftarrow L_1$	$\#L_1$	$\#L_1$	$\rightarrow L_1$	$\#L_1$

Table 4.2: Footprint of L_1.

2. $T_I = \{t \in T \mid \exists_{\sigma \in L} = first(\sigma)\}$
3. $T_O = \{t \in T \mid \exists_{\sigma \in L} = last(\sigma)\}$
4. $X_L = \{(A, B) \in X_L | A \subseteq T_L \ \wedge \ A \neq \emptyset \ \wedge \ B \subseteq T_L \ \wedge \ A \neq \emptyset \ \wedge \ \forall_{a \in A} \forall_{b \in B} a \rightarrow B \ \wedge \ \forall_{a_1, a_2 \in A} a_1 \# L_{a2} \ \wedge \ \forall_{b_1, b_2 \in B} b_1 \# L_{b2}\}$
5. $Y_L = \{(A, B) \in X_L \mid \forall_{(A', B') \in X_L} A \subseteq A' \ \wedge \ B \subseteq B' \Longrightarrow (A, B) = (A', B')\}$
6. $P_L = \{p_{(A,B)} \mid (A, B) \in Y_L\} \cup \{i_L, o_L\}$
7. $F_L = \{a, p_{(A,B)} | \ (A, B) \in Y_L \ \wedge \ a \in A\} \cup p_{(A,B),b} | \ (A, B) \in Y_L \ \wedge \ b \in B\} \cup \{(i_L, t) \mid t \in T_1\} \cup \ \{(t, o_L) \mid t \in T_O\}$
8. $\alpha(L) = (P_L, T_L, F_L)$

L is an event log over some set T of activities.The first step that we take is that we scan the event log (T_L) to see what are the activities or what are the transitions that are appear. We just look at the symbols that occur in the event log. These will be the activities in the process model, and each corresponding to a transition.Then, step 2 check which is occurred (T_I) as the first activities in some traces and T_O as the last one (step 3). The fourth step to the sixth step are the key of Alpha-algorithm.

If we think about the process discovery in terms of Petri nets, step 4, 5 and 6 are all about discovering places. As can be seen in the Figure 5.14, we want to discover places by identifying sets of transitions, A and B where A are the input of the place and B are the output transitions for the place[8].

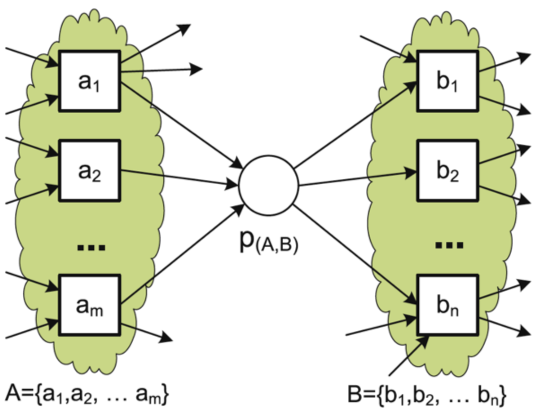


Figure 4.14: Place $p(A, B)$ connects the transitions in set A to the transitions in set B. Resource from[8].

As illustrated above, we try to find two sets of activities, A and B which should follow the following rules (step 4):

• If two activities are taken in the set A, they should never follow one another and should not follow themselves. The same applies for B.
• If any activity is taken in set A and set B, there should always be a direct succession between these two activities. So there should be at least one position in the log and that should hold for all combinations.

The 5^{th} step of the algorithm says that we should only pay attention to the sets A and B that are maximum. Because if we suppose that we have pairs of sets of activities A and B, having all these requirements, then if we remove a node in A or B or we remove the corresponding arcs, what we see then is that still the properties hold. Hence, in a way any subset of this AB relationship automatically also has the properties that we listed before.

In the 6^{th} step, P_L is the set of places. All the maximal pairs that we have just discovered in step five are the places and we add an initial place I and a final place O. So it is important to see that the really interesting part happens when we look at the sets A and B, and thereby derive the places that we want to see.

Then we take a look at the arcs (step 7), it represents all the connections from the initial place, I, to all the initial transitions in T_i. From all the transitions in the set T_o. Therefore, the transitions corresponding to the activities that happen at the end and all internal places. Internal places are represented by sets A and B and the connections are made accordingly.

Finally, In Step 8 of the algorithm, these are referred to as P_L, T_L and F_L (not P, D, F).

Let us replay the eight rules for L_1. We now have the footprint, as Table 4.2 illustrated. Then we execute the different steps of the algorithm where the key steps are steps four and steps five. X_{L1} is the set meeting the requirement of Step 4.

$X_{L1} = \{(\{a\},\{b\}),(\{a\},\{c\}),(\{a\},\{e\}),(\{a\},\{b,e\}),(\{b\},\{d\}),(\{c\},\{d\}),(\{e\},\{d\}),$
$(\{b,e\},\{d\}),(\{c,e\},\{d\}),(\{a\},\{c,e\})\}$

Here, we have found the relationship X, which contain elements that are not maximal, i.e. some of these elements are contained in other elements. Hence, we remove them which result as the following:

$Y_{L1} = \{(\{a\},\{b,e\}),(\{a\},\{c,e\}),(\{e\},\{d\}),(\{b,e\},\{d\}),(\{c,e\},\{d\})\}$

Now we have P_L:
$P_L = \{P_{(\{a\},\{b,e\})}, P_{(\{a\},\{c,e\})}, P_{(\{e\},\{d\})}, P_{(\{b,e\},\{d\})}, P_{(\{c,e\},\{d\})}, i_L, o_L\}$

The rest correspond to the internal places. Thus, the relationship can be found in the corresponding Figure 4.13.

4.5 Result

As we have huge numbers of data, it is impossible to build the process model manually. Hence, we will use DISCO (https://fluxicon.com/disco), a professional process mining tool, to discover the process model. The result of BASE and UI are as shown in Figure 4.15 and Figure 4.16 respectively.

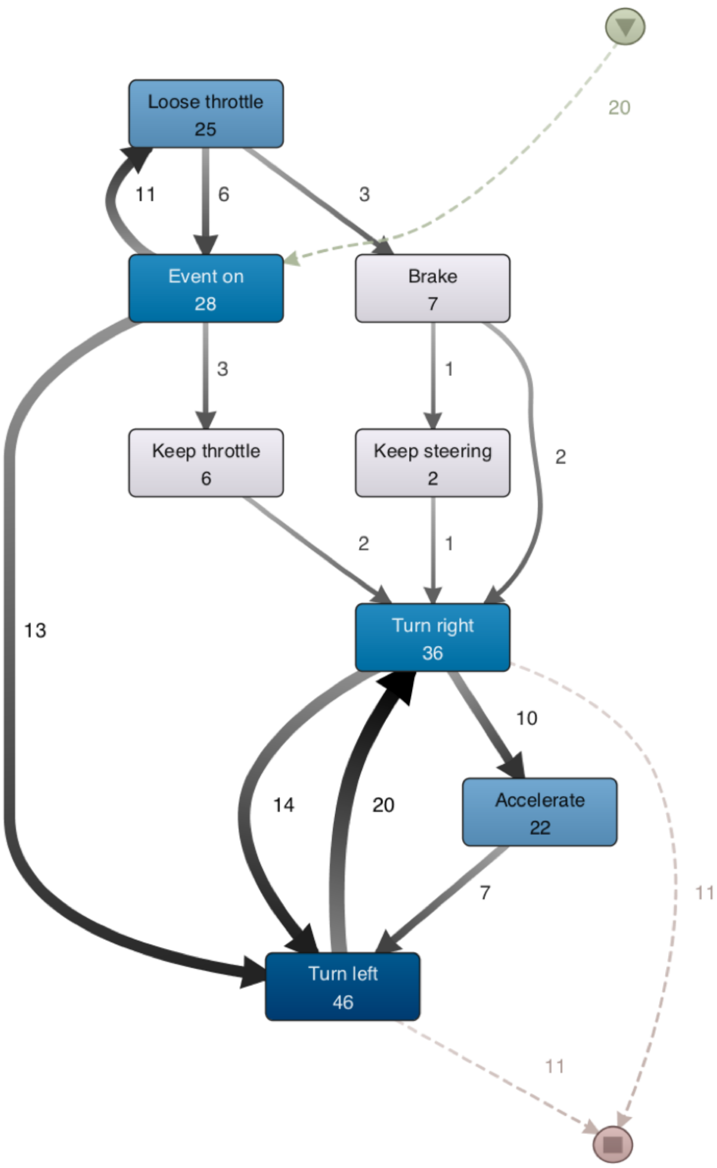


Figure 4.15: The process model of *BASE*.

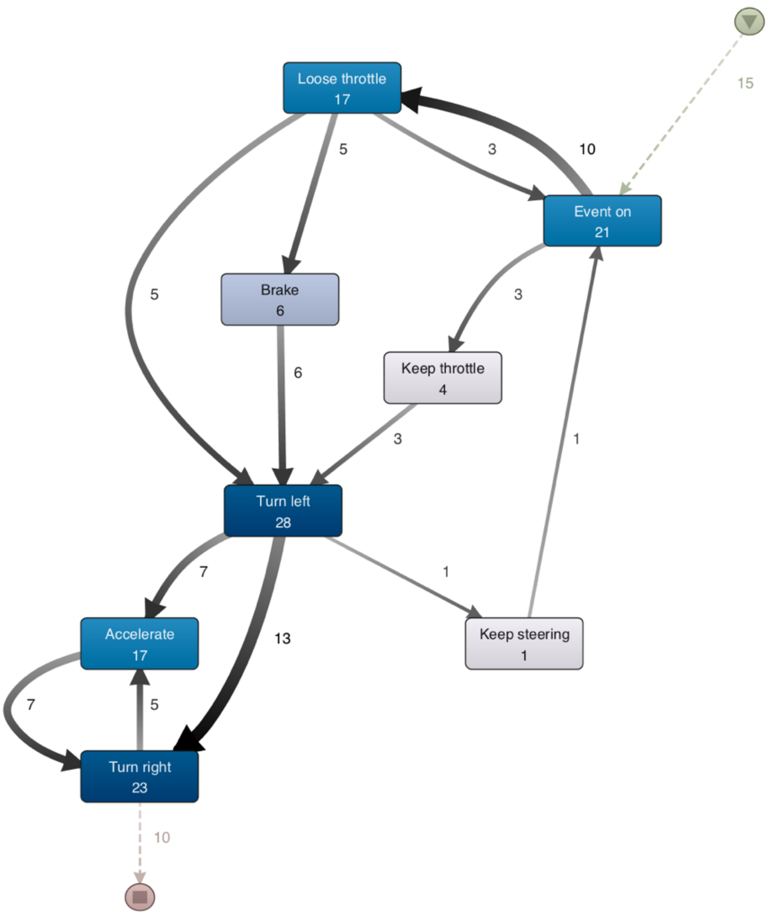
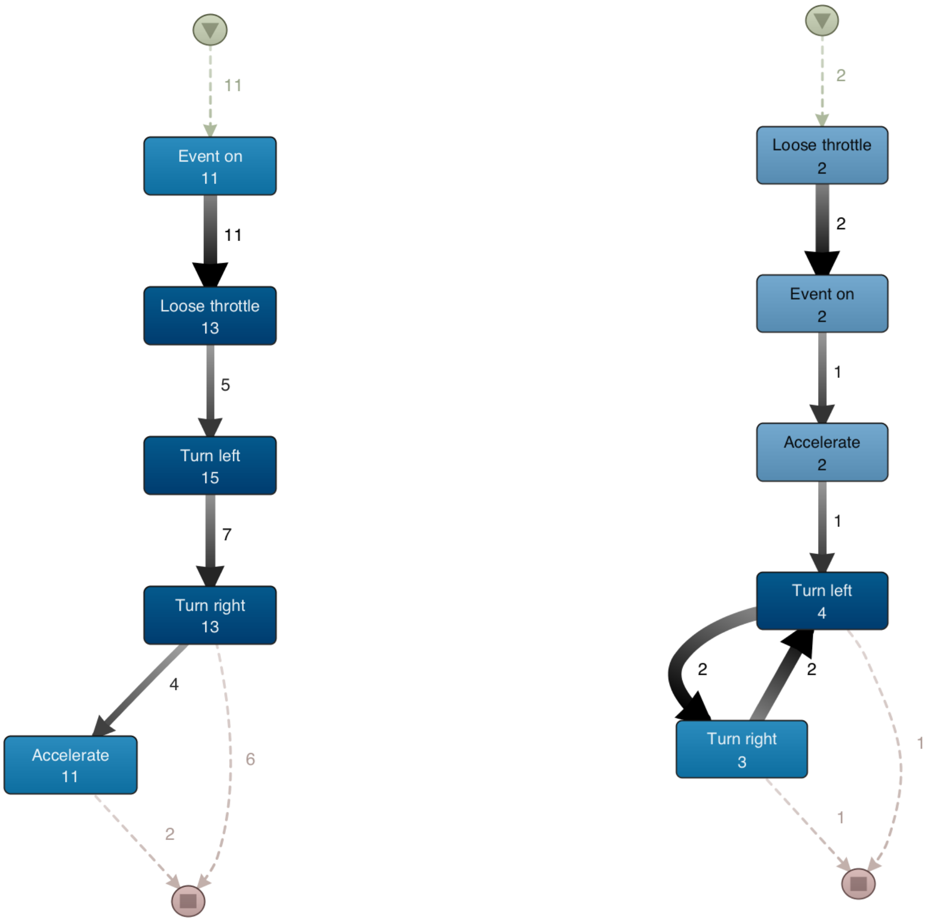


Figure 4.16: The process model of *UI*.

As shown in the both figures, the green points are the start place T_I, and the red one is the end place T_O. The blue boxes are the transitions, and the deeper the color, the higher frequency they have. Although the two models are enough for further research (for example, machine learning), one cannot intuitively find the difference between two models. If we filter the small probability events and arcs, more intuitive models which can represent the main flow of the events hidden behind the rather complex processes of figures 4.15 and 4.16, as illustrated in Figure 4.17. Compared to the BASE, participants would do something (release the gas pedal) before the emergency event happen. This confirmed that 3DATIS do made the participants' behavior change, and the most important was that it made participants behaviors safer, i.e. they slow down before the dangerous event happened. Furthermore, with 3DATIS, the *Accelerate* happens before turning the steering wheel. On the contrary, Accelerate happens after turning the steering wheel. It is probably because with 3DATIS, the speed has already slowed down, drivers need to accelerate in order to overtake the obstacle whereas without 3DATIS, drivers need to avoid the obstacle first, and then overtake.



(a) BASE

(b) UI

Figure 4.17: The filtered process model.

Besides, some other statistics can be concluded from the process mining result.

In Table 4.3, it can be seen that in each case, events with 3DATIS are less than BASE but the duration is longer. That is to say participants did each action more leisurely with 3DATIS, and they had enough time to control their car.

	BASE	UI
Events	166	117
Cases	27	21
Event per case	6.15	5.57
Activities	8	8
Median case duration	3.1s	3.9s
Mean case duration	3.7s	3.9s

Table 4.3: Statistics from process mining.

5
Conclusion

In this thesis work, three main tasks for 3DATIS have been done: design, test and analysis. In the design task, the main question was solved: how to present the sound in order to make drivers easily understand the surrounding traffic information. Then, we tested 3DATIS with 30 participants and each of them did two rounds of experiments, one with 3DATIS and one without. Two groups of behavior data were collected from the experiments. When it came to data analysis, the driving behavior of each scenario was studied. The performance of 3DATIS in *Cutin*, *Pedestrian*, *Overtake* and *Intersection* was fairly good. Especially in *Intersection* and *Pedestrian*, 3DATIS gave participants very positive indications to reduce the rate of collision and improve the TTC. However, in *Redcab*, except TTC (Time to collision), all the other indices went in the wrong direction. Most participants were not prepared and performed in panic with 3DATIS. As there were two obstacles in this scenario and one of them was the disturbance, participants could not distinguish where the sound came from and thus their judgements were interfered. Also according to the questionnaire and interview, 3DATIS was sometimes annoy when there are more than one other road user in the road at the same time. Therefore, 3DATIS can hardly exert its advantages in a relatively sophisticated traffic environment and even disturbed participants' judgement. In Chapter 4, a rather recent method called *process mining* to discover the process behind a given data set was introduced. Through process mining, the process models of scenario *Cutin* was discovered. By comparing the models with and without 3DATIS, the driving behavior with the help of 3DATIS was found to make participants behaviors safer.

The limitation of this thesis work is mainly focused on the experiment. First, there were 30 participants that took part in the experiment and this number is almost the baseline that an experiment requires. With more participants, the conclusion would be more robust and reliable. Secondly, as each participant was required to finish two experiments with the same scenarios, the learning effect cannot be totally avoided, even though the randomization of scenarios can theoretically eliminate the bias. Thirdly, the steering wheel and pedals of the simulator was designed for the game, so it could make participants feel not like driving in a real world. The consequence of which is that collected data might not reflect the real driving habit of participants.

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A

Appendix 1

INSTRUCTIONS/INTRODUCTION TO THE QUESTIONNAIRE

The aim of the study is to find out about more about you and how our 3D auditory advisory information system helps you.

Thank You!
Thank you for agreeing to participate in our study by completing this questionnaire.

Confidentiality
Some of the questions might seem a little personal, but please rest assured that they are all vital to the study and that your answers will be anonymous and treated in the strictest confidence.

How to Complete the Questionnaire
Some of the questions require that you write a response and others simply require that you select an answer from a number of options or mark a scale to indicate your response.

Instructions for driving in the simulator:

- Please keep the speed around 50 Km/h. You can go at maximum 5 km/h faster or slower
- While driving, please stay on the right lane.
- When you encounter slower vehicles, please overtake them. When you have overtaken other vehicles, return on the right lane.
- Please slow down when you see pedestrian crosses or traffic lights. You don't have to stop far away, but it is recommended that you slow down at a safe distance.

Questionnaire Part 1:
General information about you and your driving

SECTION A: General information

Year of birth: 19___

Gender:
- ☐ Male
- ☐ Female

The year you passed the driving test: (alt for how many years have you had a driving license)?

How many days per month do you drive? (Select one option)
- ☐ Less than 10 days
- ☐ 10 -20 days
- ☐ More than 20 days

SECTION B: About your hearing abilities

Have you been exposed to any loud noises within the last week, e.g. from firearms, power tools or loud music?
- ☐ Yes
- ☐ No

If 'Yes': where ....
If yes, did you use some sort of hearing protection during this event?
- ☐ Yes
- ☐ No

If you have ever carried out a hearing test, when was the last time? ....

Which statement best describes your current hearing (without hearing aid)? Circle the appropriate number.

1	2	3	4	5	x
Good		*Fair*		*Poor*	*Don't know*

How would you rate the hearing on your **left** ear?
☐ Good ☐ Fair ☐ Poor ☐ Don't know

How would you rate the hearing on your **right** ear?
☐ Good ☐ Fair ☐ Poor ☐ Don't know

Do you wear a hearing aid?

- ☐ Yes
- ☐ No

Did you have a fever within the last week?

- ☐ Yes
- ☐ No

Have you ever suffered any injury / trauma to your ears?

- ☐ Yes, namely ____
- ☐ No

Have you ever suffered from earache, ear infections or other ear disease(s)?

- ☐ Yes, namely ____
- ☐ No

Do you suffer from tinnitus or similar ear noises?

- ☐ Yes, namely ____
- ☐ No

Do you suffer from dizziness/ giddiness?

- ☐ Yes, namely ____
- ☐ No

How would you describe your experience with 3D sound? Circle the appropriate number.

1	2	3	4	5
Very familiar		*Average*		*Very poor*

Have you ever experienced any of the sound information system in cars (e.g. ….)?

- ☐ Yes, namely ____
- ☐ No

SECTION C: You as a driver

Please select which one of the following statements best describes you as a driver. If none seems to fit exactly, just select the one that is closest. *Please select only one*.

- ☐ I do not particularly like driving and can sometimes be a little nervous; however I will drive when necessary.
- ☐ I am a skilled driver and drive fast but safe.
- ☐ I love to drive fast, even if it is a little dangerous at times.
- ☐ I am a competent and careful driver and do my best to stick to the speed limit

Questionnaire Part 2:
After the training

Question 1: What does the sound do, you think?

Question 2: Sometimes the sound gets louder, do you have any ideas as to why?

Question 2: Sometimes the rhythm changes, do you have any ideas as to why?

Question 4: What do you think the of direction and movement information from the 3D sound system?

Questionnaire Part 3:
After the test

What is your current occupation?

☐ I work, this is my work title: ____________________________________

☐ I study the following ________________________
Level:__________

☐ Other, namely: ____

What is your highest Education Level completed:

☐ Less than High School (Grundskola eller mindre)
☐ High School (Gymnasiet)
☐ Some University (En del universitetsstudier, men ingen examen)
☐ Bachelor Degree (Kandidatexamen)
☐ Master's Degree (Högre examen motsvarande 4,5-5 års heltidsstudier, exempelvis
en masterexamen, civilingenjörsexamen, civilekonomexamen eller liknande.)
☐ Doctoral Degree (Doktorsexamen)

How would you rate the 3D sound information system in terms of the following scale?
Put an 'x' in the appropriate slot.

Useful |__|__|__|__|__| Useless

Pleasant |__|__|__|__|__| Unpleasant

Bad |__|__|__|__|__| Good

Nice |__|__|__|__|__| Annoying

Effective |__|__|__|__|__| Superfluous

Irritating |__|__|__|__|__| Likeable

Assisting |__|__|__|__|__| Worthless

Undesirable |__|__|__|__|__| Desirable

Raising Alertness |__|__|__|__|__| Sleep-inducing

Please mark the sector(s) from which the sound information was ***helpful***.

(front of car)

(Back of car)

Please describe in just a few words why:

Please mark the sector(s) from which the sound information was ***confusing***.

(front of car)

(Back of car)

Pleas describe in just a few words why:

Questionnaire Part 4:
Post interview questions

How do feel about the sound design? Any suggestion?

Was there any information that you felt was redundant or unnecessary?

Is there any information you were missing?