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A Fuzzy Logic Based Approach to Evaluate Driving Manoeuvres: An Integrated Approach to Improve Training

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Abstract—Driver training is one of the interventions aimed at mitigating the number of crashes that involve novice drivers. Our failure to understand what is really important for learners, in terms of risky driving, is one of the many drawbacks restraining us to build better training programs. Currently, there is a need to develop and evaluate Advanced Driving Assistance Systems that could comprehensively assess driving competencies. The aim of this paper is to present a novel Intelligent Driver Training System (IDTS) that analyses crash risks for a given driving situation, providing avenues for improvement and personalisation of driver training programs. The analysis takes into account numerous variables acquired synchronously from the Driver, the Vehicle and the Environment (DVE). The system then segments out the manoeuvres within a drive. This paper further presents the usage of fuzzy set theory to develop the safety inference rules for each manoeuvre executed during the drive. This paper presents a framework and its associated prototype that can be used to comprehensively view and assess complex driving manoeuvres and then provide a comprehensive analysis of the drive used to give feedback to novice drivers.

Index Terms— Driver Training, Novice driver, Crash prevention, Intelligent Driver Training System (IDTS)

I. INTRODUCTION

DRIVERS are at a greater risk of crashing during the early years of driving. Research indicates that novice drivers are over represented in crashes [1] and that these crashes have different characteristics compared to the ones from experienced drivers: these drivers are particularly involved in single vehicle crashes involving loss of control, excess speed for conditions, unlit rural roads and crashes while making cross-flow turns [2]. Young driver crashes are often due to a lack of experience, poor hazard perception practice, and a tendency to take risks, as they drive faster, in ways that increase the probability of conflicts with other drivers and with smaller gaps [1, 3, 4].

Knowledge about what are the subjective and objective characteristics of safe and unsafe driving is extensive [16-18]. Up till now a lot of driver feedback programs have been designed, each trying to cover as many aspects of driving as possible [19, 20]. Yet to our knowledge, there is no comprehensive automated feedback system that lets the drivers and driver trainers to effectively observe and measure all the variables relevant to safety involved in driving (i.e. Driver, Vehicle and Environment). The aim of this paper is to design a new, objective and automated way of providing feedback to instructors and/or novice drivers by harnessing and combining data captured from various in-vehicle sensors from on-road training. This paper provides a proof-of concept and a demonstration of how this system would technically work in principle. Such a tool could be used to improve training of novice drivers by providing a comprehensive analysis of the risk of the manoeuvre as performed by the novice driver, as well as a way to highlight the specific deficiencies of the novice driver for further tailoring the training of the driver.

The next section will provide the background supporting the proposed approach. Then we will comprehensively present the approach for developing Intelligent Driver Training System and its prototype.

II. BACKGROUND

A. Novice driver issue related to road safety

There is a long research debate about whether the over-representation of young drivers in road crashes arises because of immaturity or because of inexperience [5]. Young drivers underestimate the risks and overestimate their driving skill; they also consider themselves superior to other drivers. Such overestimation may partly be an effect of training strategies, particularly for programs providing advanced skills training for facing dangerous situations. This is an issue as drivers do not drive more carefully than they believe is necessary, which means that such drivers would take more risks.

B. The driver training debate

More generally there is a debate on the effectiveness of driver education programs in the literature [6]. Numerous studies have failed to show any positive effects of driver education and training programs on crashes and violations, and some even suggest that such programs pose a safety risk, whether due to earlier licensure or overestimation of skills. Difficulty in showing the positive effects of driver training on crashes

reduction should not reduce efforts to improve training strategies, as many of these studies are methodologically flawed (for instance due to lack of control group or confounding effects) and as the validity and usefulness of crash rates as a measure of effectiveness is questionable, crashes being rare events, under-reported and the result of multiple contributing factors [7]. This refrains from drawing definite conclusions and further and more robust research is needed.

One possible explanation for the lack of positive effects of training program could be the fact that these programs did not focus on the important factors leading to risks of collisions. Efforts to improve novice driver safety should focus on attitudes and beliefs of drivers [8]. Traditions in driver training must be changed or complemented, particularly by focusing on the aspects of the driving task relates to the risk of collisions and making drivers aware of the practical limitations of the skills they have learnt [4]. This can particularly be done by putting an emphasis on hazard recognition and risk assessment [6]. In particular current technology developments allow the use of computer based training strategies providing dynamic visual context to learners, which have been shown to help in proceduralising new skills developed during training (earlier glances toward hazards in this study) [9]. An important method of improving safety among young drivers may therefore be to find ways of making them aware of their own limitations and risks associated to a particular manoeuvre [4]. Such an approach could result in enhanced decision making by novice drivers. To put this into practice, Robinson [10] advocates for the development of training programs that would be empirically based, focused on perceptual skill deficiencies, tackling over-confidence by making novice drivers aware of their limitations and should be tailored to the particular skill deficiencies of each novice driver. Training strategies should also be designed to counteract the likelihood of novice drivers developing overconfidence in their driving skills [1].

C. Current approaches and their limitations

The current approach to improve novice driver safety relies on graduated licensing and on parental involvement. Advanced Driving Assistance Systems (ADAS) could be a solution for improving novice driver safety, as they could be used to provide objective and contextualised information to both trainers and trainees. Indeed, current practice by professional driver trainers is mainly manual, which is prone to subjectivity, potential lack of identification of multiple hazards, and a lack of comprehensive environmental context. So far, most intelligent systems have focused on warning the driver of potential hazards or lane departures by fusing data from multiple sensors [11-14]. However, prioritisation of the warning system is not the appropriate solution for tackling the novice driver issue, as such systems tend to results in a false perception of control and lack of urgent reactions by novice (and particularly male) drivers [13] or in distraction, both resulting in higher crash risks. A better approach would be to use the fusion of information to assess the level of risk of a particular driving manoeuvre, and then provide interactive feedback to the novice driver so that they can identify their limitations. Some attempt toward this approach can be found in a study using low cost sensors (smartphones) to assess safety of the driving task [15], but with a lack of theoretical modelling of what is a safe manoeuvre and the limitations of the sensor used for integrating the road environment in the assessment of risk.

Research suggests that the best learning environment for the inexperienced driver is the real road system under the supervision of an experienced driver or an instructor [1, 3]. One of the key aspects of driver training programs is assessment or feedback on the driving performance. This can be either self-assessment or assessment from another group or individual.

D. The potential of an integrated approach to improve driver training

The driver's decision and response on processing the stimulus is not accurate but rather an estimate. By exploiting fuzzy set theory we will be able to model the low risk driving behaviour. We hypothesize that training results in increased accuracy of the driver estimates that are required in execution of different driving manoeuvres. Therefore an effective feedback system needs to be in place.

In-order to comprehensively tackle driving issues, a complete and integrated framework needs to be developed that should include and examine all the parameters that influence driving (i.e. cues related to road, vehicle and driver). This introduces the need for a system that can assess the multiple manoeuvres in a driving scenario as high risk or low risk based on the parameters acquired from DVE. Once the assessment has been made, an effective feedback system needs to be put in place that can help driver trainers to better explain the driving shortcomings of novice trainee drivers. This can take the form of a visualisation system (the approach taken in this paper), as this has the potential benefits of feedback support, given the assertion that people are trying to learn or reduce the error inherent to their early attempts of performing a particular manoeuvre. This paper focuses on decomposing, analysing and providing feedback about manoeuvres such as driving on curves, overtaking and lane changing. Fuzzy set theory is then applied as the framework for risk evaluation and analysis of the manoeuvres, as this theory was developed to represent imprecise knowledge and concepts and has been successfully used in many real world applications due to its flexibility (such as automatism, robotic, informatics, decision making problems, medicine and pattern recognition), as they enable the representation of imprecise knowledge and concepts. In particular, it can be implemented in real-time and with an appropriate structure for effective risk modelling [21].

Figure 1 illustrates three sensors, namely FaceLab (eye tracking system), MobileEye (lane and obstacle detection system) and Vigil System (GPS, accelerometer and vehicle dynamics data logger) to gather data from the DVE.
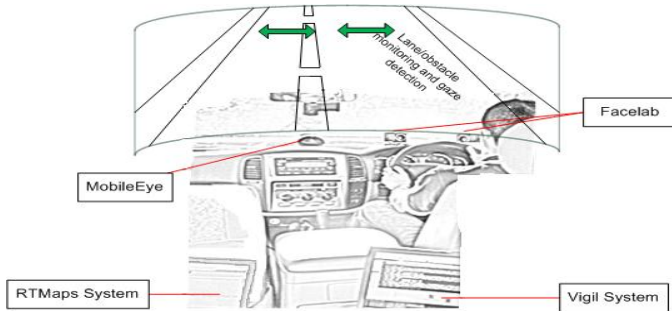
Fig. 1. Multi-sensor recording system for Intelligent Driver Training System (IDTS)

III. IDTS FRAMEWORK

A successful feedback solution has to combine the benefits of multiple sensors such as GPS, accelerometers, cameras, vehicle information, driver's head/eye data and geographical data. In order to obtain a precise synchronization, a sufficiently accurate global time for all sensors and fusion system is necessary. This would then allow processing of drive related data using complex algorithms to retrieve information such as but not limited to; following distance during particular manoeuvres, indicator distance before manoeuvres, average speed during manoeuvres, excessive braking or accelerations, driver gaze depth and orientation etc. All this information synchronously plotted on an interactive map will definitely complement the effectiveness of the contextually rich feedback system.

The proposed framework (i.e. Intelligent Driver Training System) using fuzzy logic provides crash risk assessment for the driving manoeuvres. We call the IDTS presented in the paper a framework, as many of its components can be replaced or extended. For example, the risk evaluation modules could be based on statistical classifiers. The library of manoeuvres is also extensible. Along with this, the framework utilizes an interactive mapping interface to provide feedback of the drive to its users. This would eventually help driver trainers and parents to objectively evaluate and provide feedback to novice drivers.

To model a complex driving scenario in a comprehensive way, it is necessary to fuse several sensory data. Our test vehicle (a 4WD) is equipped with vision systems, and sensors to monitor the vehicle dynamics as described in Figure 1. Currently the test vehicle for this project includes the following sensors.

- FaceLab (head and eye tracking system) [see 22].
- MobileEye (lane and obstacle detection system) [see 23].
- Vigil System (GPS, accelerometers and vehicle dynamics data logger) [see 24].

Figure 2 presents the block diagram of the architecture of the IDTS. All outputs are gathered from the above mentioned sensors during the drive and then RTMaps is used to synchronize all the sensory data. By integrating information about the vehicle, driver and environment we are able to contextualize, observe and assess formally a more complete range of driver behaviours. After the data synchronization, manoeuvres are segmented out as right turn, left turn, lane change and overtake. Each manoeuvre is composed of several individual tasks that are necessary to be performed in a timely manner. This sequence of task completion helps driver trainers to assess the drivers during execution of different manoeuvres. The IDTS uses fuzzy rules to evaluate the risk associated with manoeuvres. Finally, it uses a mapping module combined with graphical representation of the drive to provide an extensive feedback about the drive. Currently, the IDTS is able to segment and assess risk for the following manoeuvres: turns, lane changes and overtakes. An example of a standard manoeuvre assessment (i.e. right turn) that driver trainers use is presented in Table I. The assessment tables for lane change and overtake have similar tasks as described in section 3.1.1.

The tasks are basic actions that are required to drive safely and are part of many manoeuvres that drivers carry out during their drive. For example: the 'check mirrors' task in 'turn' assessment is also required before the start of 'lane change'. And 'lane change' is a requirement of overtake manoeuvre. So we can see how the IDTS architecture is based on combining basic behaviours/tasks to build more complex behaviours/manoeuvres. The breakdown of particular manoeuvres (i.e. curve, lane change and overtake) into tasks and risk assessment (i.e. low risk or high risk) of these tasks is explained in detail in the manoeuvre respective sections.
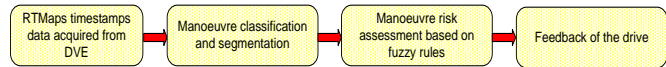

Fig. 2. Top level architecture of the IDTS

TABLE I
DRIVER EDUCATION PERFORMANCE-TURN ASSESSMENT

(Example of) DRIVER EDUCATION PERFORMANCE
Right Turn Assessment (Tasks List)
1) Checks mirrors.
2) Positions car properly in lane.
3) Signals right at the right distance from turn start.
4) Reduces speed and keeps wheels straight.
5) Checks traffic thoroughly, yielding to pedestrians.
6) Starts turn.
Source: Michigan Department of Education (1997) [25]

A. Data synchronisation

In-order to comprehensively assess a driving situation, it is necessary to have a spatiotemporal analysis of the data. The task of fusing sensory data input is handled by RTMaps. It timestamps and synchronizes the sensor inputs from MobileEye, Facelab, cameras and VigilSystem for the drive. It then stores the data for future real-time replay. The synchronized drive data enables us to measure task durations during manoeuvres (e.g. the amount of time host vehicle remained in the right lane during overtake manoeuvre). The duration required to complete a specific task is an important,

safety-relevant measure. These parameters are later used in risk assessment of a particular manoeuvre.

B. Segmentation of Manoeuvres

A typical driving scenario would comprise of a certain set of driving events and patterns that are repeated over time. For example, a right turn manoeuvre is composed of tasks as shown in Table I. The important aspect of manoeuvre risk assessment is to segment out particular manoeuvres from the drive. In-order to effectively monitor the driver behaviour, every manoeuvre is divided into three parts namely: pre-manoeuvre, manoeuvre and post-manoeuvre. This helps to objectively assess the driver behaviour not just during manoeuvre but even at the approach and end of a particular manoeuvre.

The manoeuvres are chosen because of their cost to the society in case of crash. In Australia, 30% of crashes occur on road curves [26]. Crashes on road curves frequently result in fatal injuries or casualties. Curve related crashes contributed to 63.44% of fatalities [27]. In addition, the likelihood of surviving crashes on curved roads is approximately 17% lower than on straight roads [27]. The other manoeuvre under consideration in this paper is overtaking. Overtaking is considered to be a hazardous task, experts estimate that lane change crashes including overtaking and lane merging account for 4 to 10% of all crashes [28].

1) Manoeuvres (Turn and Overtake)

As previously mentioned, the manoeuvres are segmented based on the spatiotemporal location of the vehicle. For example in order to determine whether the vehicle is passing through a turn, GPS data are used. This GPS data helps to compute a turn angle for each GPS point returned for the drive. Details are explained in [29]. The start and end of the turn manoeuvre are identified, which helps to better monitor driver behaviour just before and after negotiating the turn. The IDTS framework utilizes the same tasks (as presented in Table I) for risk assessment using fuzzy rule based system.

Apart from the calculation of turn angle for the vehicle, the position of the vehicle with respect to the lane is also calculated. This enables the system to determine the location at which the lane changes take place. Table II presents the tasks that driver trainers assess during an overtake scenario. Since there are number of events that frequently occur during driving, a typical driving scenario would comprise of a certain set of driving events and patterns that are repeated over time.

As apparent from Table I and Table II, the two distinct manoeuvres are composed of multiple tasks. These tasks might vary slightly based on a manoeuvre but the basic principle of these tasks is the same in both manoeuvres.

TABLE II
DRIVER EDUCATION PERFORMANCE-OVERTAKE ASSESSMENT

(Example of) DRIVER EDUCATION PERFORMANCE
Overtake Assessment (Tasks List)

1) Checks mirrors.
2) Positions car properly in left lane.
3) Maintains speed limit
4) Looks in the right lane where the driver is going to move
5) Signals right at a sufficient distance before lane change
6) Turns into the right side lane smoothly
7) Crosses the car which is now on the left.
8) Checks mirrors
9) Positions car properly in right lane
10) Maintains speed
11) Looks to the left lane where the driver is going to move.
12) Signals left at a sufficient distance before lane change
13) Turns into the left side lane smoothly completing the overtake manoeuvre

Source: Overtaking - Driving test tips [30]

2) Manoeuvre Classification

For clarity, it should be stated that "low risk" behaviour is not a tangible or easily defined construct and therefore a definition of "low risk" behaviour is developed that will be made operational within this project. An example of a core driving competency may relate to maintaining a safe driving distance between vehicles, and braking on approach to an intersection. A computer based analysis of the above basic behaviour can be articulated into a safety scale.

The main idea behind the classification of manoeuvres is that given information about the driving situation (i.e. tasks executed), and knowledge about driver behaviour, it is possible to infer the manoeuvres that a driver is most likely to have performed. Figure 3 introduces a pictorial representation of the manoeuvre risk assessment. For example, when the framework identifies a lane change manoeuvre, risk assessment of lane change is performed. This risk assessment is based on tasks such as

• What was the driver speed on approach of the lane change manoeuvre?
• Did the driver check the lane (by doing a head check) in which they were going to move?
• How long before the indicator was switched on before the lane change?
• Was the driver positioned in the lane properly before the lane change?

Another point highlighted in Figure 3 is that task assessments can be combined to create a manoeuvre assessment (represented as triangles). And some of the manoeuvre assessments can be further combined with other manoeuvres or tasks to create more complex manoeuvres' assessments (i.e. T-Crossing or overtake).

The benefit of such a modular approach is that it facilitates the evolution of further complex manoeuvres. It has been mentioned above that the IDTS framework utilizes fuzzy set theory to define low risk driving models for different

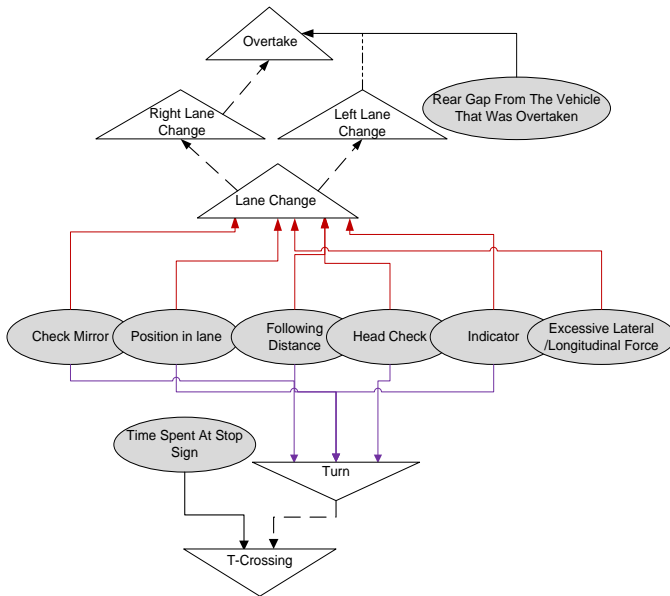manoeuvres. Details are explained in the following section.

Fig. 3. Manoeuvre risk assessment based on the tasks. Tasks are shown in ellipses and manoeuvres are represented as triangles.

C. Risk Assessment based on Fuzzy Logic

This section deals with creating a low risk driving model based on fuzzy set theory. All of the driver inputs while driving are not based on crisp values; rather they have some uncertainty based on subjective perception (e.g. distance from the object in front etc.).

At the empirical level, uncertainty is an inseparable companion of almost any measurement, resulting from a combination of inevitable measurement errors and resolution limits of measuring instruments [31]. Fuzzy logic has been proven to deal with these uncertainties [31]. Fuzzy logic uses rules for inference of results. A fuzzy rule has two components: an if-part (antecedent) and a then-part (consequent):

IF{antecedent},THEN{consequent}

For instance, Table III presents the inference rules between the two sets, which are:

The distance at which the indicator was switched on before the turn (1st set).

and

Average speed of the car on the approach of a turn (2nd set)

Figure 4 shows the trapezoidal fuzzy membership functions for the 1st set which are Very Low (VL), Medium Low (ML), Medium (M), Medium Large (MLrg) and Very Large (VLrg). And Figure 5 shows the pictorial representation of the membership functions for the 2nd set. Those are Low (L), Medium (M) and High (H). One of the rules in Table III for 'High' average speed and 'Very low' indicator distance before the turn implies 'Very high' risk and can be written as:

IF{average_speed=='H'AND distance=='VL'}THEN{Risk_is_VeryHigh}

This rule based system introduces a quantifiable degree of uncertainty into the modelling process in-order to accommodate the natural or subjective perception of real variables [32]. It models the human decision making process using fuzzy membership functions and fuzzy rules (if/then rules). The formation of the rules is based on advice from the human expert (i.e. driver trainer). In-order to construct these rules, multiple negotiations of the same manoeuvre were reviewed.
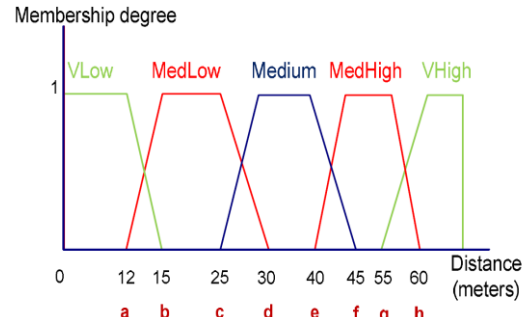

Fig. 4. Trapezoidal Membership functions for indicator switch on distance before the turn
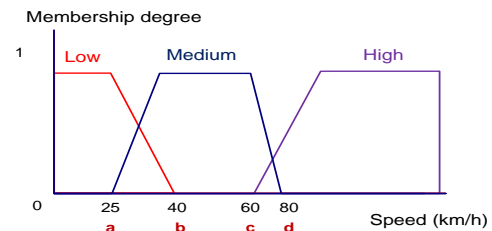

Fig. 5. Trapezoidal Membership functions for speed on approach to a turn

1) 'Indicator' risk assessment

As previously mentioned, the manoeuvres are segmented based on the spatiotemporal location of the vehicle. Such segmentation can then be used, for example, in order to determine when the vehicle is passing through a turn.

Table III along with Figure 4 and 5 are utilized to assess the risk for "Indicator" task (displayed in Figure 3). This assessment is a necessary component to assess multiple manoeuvres (i.e. turn, overtake, T-crossing etc.) risk. In Figure 4, the X axis represents the membership functions and their relationship for the fuzzy set (indicator switch on distance), whereas the Y axis presents the degree of membership to the functions (i.e. VL, ML, ..., MLrg etc.). The risk is evaluated on a scale of 0-1, 1 being the highest risk.

Table III presents the fuzzy rules for indicator risk assessment. This risk is calculated by comparing the 'safe distance' (distance between indicator switch on location and the point of turn start) against the average speed of the vehicle before turn manoeuvre.

The rows (in Table III) depict average speed of the vehicle to the start of a turn. The fuzzy membership functions for the average speed are (Low (L), Medium (M), and High (H)). Low speed fuzzy function is defined between 0-20 km/h.

Medium is defined between 40-60km/h and speeds above 80km/h are considered 'High'. Figure 5 presents this in pictorial form. The columns in Table III represent the 'safe distance'. The 'safe distance' is described by fuzzy membership functions (VL, ML, M MLrg, VLrg). These membership functions emphasize that indicator should not be turned on very close or very far from turn start. Figure 4 shows this in pictorial form. Some fuzzy rules in Table III are:

IF{average_speed=='M'AND
distance=='M'}THEN{Risk_is_VeryLow}

IF{average_speed=='H'AND
distance=='VL'}THEN{Risk_is_VeryHigh}

Table IV below introduces the fuzzy sets involved to assess risk for the remaining tasks/manoeuvres shown in Figure 3.

These assessments eventually help the IDTS framework to flag any task in a manoeuvre that the driver might have not performed in a low risk manner.

Another integral part of the driver training system is feedback about the drive to the driver. This feedback can be from a driver trainer or self-assessment. In-order to give effective feedback to the user, flags are placed on the approach, during and at the end of the recognized manoeuvres. The colour of flag varies from green (Very Low risk) to red (Very High risk).

TABLE III
INFERENCE RULES FOR INDICATOR RISK ASSESSMENT USING AVERAGE SPEED AND THE INDICATOR DISTANCE

Avg. Speed (km/h)	Safe Distance (meter)		
	Med	**M High/M Low**	**V Low/V Large**
Low (L)	Low_Risk	Low_Risk	High_Risk
Medium (M)	VeryLow_Risk	Medium_Risk	High_Risk
High (H)	Medium_Risk	Medium_Risk	VeryHigh_Risk

TABLE IV
INFERENCE RULES FOR RISK ASSESSMENT DURING A LANE CHANGE MANOEUVRE

Tasks	Fuzzy sets	
Position in Lane	Vehicle position *w.r.t. right lane for the manoeuvre *w.r.t: with respect to	Vehicle position *w.r.t. left lane for the manoeuvre
Check mirrors	No. of times mirrors are checked before undertaking of a manoeuvre	
Following distance	Following distance maintained with the car in front on the approach to a manoeuvre Versus average speed	
Head checks	No. of times side of the vehicle is checked (i.e. head check) before undertaking of a manoeuvre. Plus how far was the driver looking on the road when negotiating the manoeuvre.	
Excessive accelerations /decelerations	No. of excessive accelerations or decelerations during the manoeuvre.	

D. Comprehensive Feedback Using Mapping

Visualization of the drive is an integral part of providing feedback to the driver. Since the end users of IDTS are driver trainers and trainees, it is necessary that all recorded drive data and risky situations are represented in an easy to comprehend manner. A comprehensive graphical mapping of the data collected during the drive makes it certain that the data collected and processed is not just organized information but rather actionable intelligence (Figure 6).

Figure 7 (detail of display 4 of Figure 6) below shows a part of the comprehensive feedback module. The X axis shows the distance travelled by the vehicle. Y axis from 0 till '100' shows driver's speed (km/h) and scaled down average gaze depth (in meters). Further above on Y axis, the points highlighted are indicators, points where brakes were applied, vehicle turned, lanes were changed, overtake manoeuvre, excessive acceleration or deceleration and driver checked rear or side mirrors. Another feature is, if these manoeuvres were performed in a high risk manner the identification labels of these manoeuvres change colour from blue to red (as shown by the legend in Figure 7).Using such a graphical interface, driver trainers and trainees will be able to empirically check multiple driving parameters for a particular time.

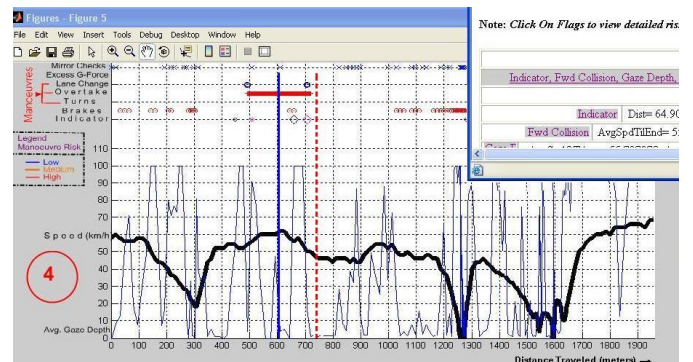Fig. 6. The comprehensive feedback module with four displays.

Fig. 7. Details of display 4 of the IDTS.

But the graph presented in Figure 7 alone does not allow accessibility to view road parameters (e.g. the location of an intersection, location of a roundabout etc.). In-order to handle this issue, the IDTS provides a map in the feedback module. Since all the drive information (from DVE) is recorded in a synchronous manner, it is possible to display the vehicle position along with the driver gaze points on a map (i.e. GoogleMap) for any given time. Along with this, by clicking any vehicle trajectory point on the map, the framework is able

to display its corresponding location on the drive's graphical representation (Figure 7). The map also flags the manoeuvres that were performed in a high risk manner.

One of these flags is visible in the Google map in Figure 8 (display 2 of Figure 6). The Feedback module in Figure 6 has four display panels. They are:

1. The main controller. Display 2, 3 and 4 present the driving scenario for the slider selected time.

2. Interactive map (i.e. GoogleMap) that displays the recorded vehicle trajectory (red line).

   • The position of the vehicle (i.e. the car icon), drivers' gaze direction and depth (in green dots and lines), indicator usage (yellow star), excessive accelerations/decelerations.

   • The flags display risks at which a manoeuvre is performed. On clicking the flag, a table appears (shown at bottom of display 2). This table displays the manoeuvre and the risk of each task (shown by variable 'FuzzScr') within that manoeuvre. Risk is normalized between 0 and 1, where 1 is the highest risk.

3. The camera image (displaying the road ahead) overlaid with the driver's gaze points.

4. The graphical representation of the complete drive. The solid blue vertical line displays the position of car based on the slider selected time. The vertical red dotted line corresponds to the point clicked on the vehicle trajectory displayed in Google map. This allows the driver trainers to view the position of road landmarks (traffic lights, roundabouts etc.) on the drive's graphical representation (display 4). This helps to assess behaviour such as did the driver change lane while crossing the traffic light?

Fig. 8. Details of display 2 of the IDTS.

This effective and dynamic feedback will help the driver

trainers to better empirically assess (both weaknesses and strengths) the drives. Along with this, comprehensive feedback will allow the drivers to self-assess their manoeuvre undertakings.

IV. CONCLUSION

Driver training programs have been mainly developed without clear theoretical foundation [33]. A comprehensive and systematic evaluation of the drive could help to understand the empirical differences in novice and experienced driver behaviours. This would not only help the driver trainers to better understand different driver behaviours that they otherwise wouldn't be able to identify, but also assist them to design programs that improve these behaviours.

This paper presented a framework and its implementation for analysing crash risk for a set of driving manoeuvres. The

The IDTS framework integrates information related to driver, vehicle dynamics and road information. It then segments out the complex driving manoeuvres and uses expert's knowledge (i.e. in the form of fuzzy rules) to assess the risk of tasks within each manoeuvre. It then uses a contextually rich interface to provide feedback of the drive. The dynamic assessment module combines risk assessment of multiple tasks to identify the risk of a manoeuvre. This flexible design makes it possible to combine multiple simple manoeuvres/tasks into complex manoeuvres.

This framework will help identify and sharpen driving abilities that are required for skilled driving. Diversions made by trainees from the experienced model of driving will flag areas where improvements need to be made in-order to aid and support novice drivers. It will act as an assisting tool for the driver trainers and trainees to identify the driving competencies required and understand shortcomings on part of novice drivers.

Eventually both drivers and driver trainers would be able to assess driving performance using the IDTS. As already mentioned, a major percentage of road crashes are attributable to driving error. Thus, driver training remains an important road safety intervention to improve driving performance and abilities, particularly amongst young drivers.

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