Contribution to 30th European Annual Conference on Human Decision-Making and Manual Control (EAM 2012), 11. September 2012, Braunschweig, Germany

Driver intention modelling for partly automated vehicles- The benefit and necessity of a driver and situation adaptive approach

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Introduction

Partly automated vehicles like shown in the HAVEit project [6] can be seen as a bridge towards self-driving vehicles as known from Google [5] or BMW [3]. Partly automated vehicles still take over control in lateral and longitudinal direction but additionally involve the driver. This is an advantage compared to fully automated vehicles in case the automation fails and the driver has to take over. As the BASt pointed out in its last report [1] this is a main reason while partly automated vehicles would get a licence in Germany in contrast to fully automated vehicles. Since the human is embedded in the control loop cooperation is a cornerstone of partly automated vehicles. Cooperation works if both the human and the machine follow same intentions. A discrepancy in their intentions leads to conflicts in the human machine interaction as described in [2]. Clearly, conflicts are decreasing the acceptance and the stability of the system. Therefore it is essential firstly to detect conflicts and secondly to develop strategies to solve them. This is the part where driver intention modelling becomes mandatory. Knowing driver's intention means knowing the potential for a conflict. Moreover it allows to adapt automation behaviour to the driver and thus to reduce the conflict potential. Driver intention modelling is therefore closely linked to adaptive systems.

In [2] an adaptive system a driver intention model is already prototypically implemented as an instrument of conflict prevention. The idea is to detect the potential of a conflict by driver's activity. More precisely if the activity is high than the system shifts temporarily control to the driver by executing a transition from the automation level “Partly Automated” to “Driver Only”. In other words driver's activity is interpreted as a driver's disagreement with the automation behaviour. In contrast to an overriding the automation takes over control if the activity goes down again as an indicator that the driver agrees with the automation. The explicit research question now is, if the driver intention model has to be adaptive to any driver or is a model based on an average driver sufficient as long as the transparency of the system behaviour is guaranteed. Therefore two usability studies were carried out. Results are discussed in section 2.3. The next section will describe briefly the two implemented driver intention models.

Driver intention modelling

The involvement of the driver in “Partly automated” is characterized by strong but not fully autonomous control of the automation in lateral direction. Thus the driver has to steer a little bit in curves, as in [2] explained. Therefore a general requirement for both models is the ability to distinguish between steering and a requested transition.

Input variables

The input variables are split into the lateral and longitudinal direction. The longitudinal direction considers the moment on the brake pedal and on the acceleration throttle. The variables of the lateral direction are the steering moment and the gripforce. Empirical research done before showed that for small lateral acceleration the moment on the brake pedal and on the acceleration throttle are the most important variables because the driver shows his activity only through this two variables. There is hardly any steering activity. In the situation of a high lateral acceleration (like in curves) the longitudinal variables become less important and the steering moment and gripforce together become more important. The gripforce plays an important role as a global variable. Without the gripforce changes in the automation level in straight and curvy road segments become less intuitive.

Non-adaptive approach

Figure 2-1 (left) shows the concept of the non-adaptive approach. The algorithm receives the measured values as described in section 2.2.1 and chooses based on logical rules the desired automation level. Logical rules are based on "AND" and "OR" compositions. It depends on the current automation level which logical function is considered. If the current automation level is “Driver Only”, the "AND" function is used, otherwise the "OR" function. If the driver is in the automation level ”Partly Automated” the driver has to show more activity only on one of the four measured values to change to the automation level “Driver Only”. On the other hand if the driver is in the automation level “Driver Only” the driver has to show less activity in all measured values simultaneously to change to the automation level ”Partly Automated”. The saved characteristic values, which are compared to the measured values to decide about the automation level, are constant values. They are calculated for an average driver. Therefore the approach is not adaptive.

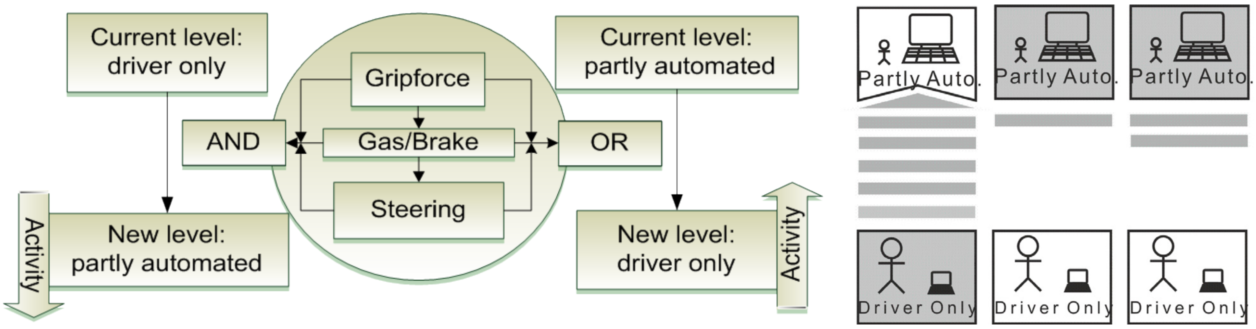

Figure 2-1: Left: Design of the non-adaptive approach. Right: Visual display with an example sequence of a transition. The number of bars depends on the current activity and shows the likelihood for a transition

Adaptive approach

The adaptive approach is more sophisticated. The approach uses the machine learning method fuzzy logic [4]. The background for using this method is because human thinking can be better described with speech rather than with numbers and formulas. That makes it easier to understand and more transparent for humans compared to neuronal networks.

Trapezoid estimation: A central point of fuzzy logic is to calculate the shape of the fuzzy sets. In this case the edges (a, b, c, d) of trapezoids have to be computed. For the approach three fuzzy sets/trapezoids are used (small, middle, high). The calculation structure is shown below. In the first step the sets will be separated sharply. Therefore the minimum, maximum and the mean value of the dataset will be extracted. A partition parameter is chosen to create the three sharp sets depending on the values Δmin, Δmid and Δmax. Additionally, for each sharp set a histogram is build. The interval containing the most values represents the trapezoid values for the membership value one. The next step calculates the trapezoid values of the overlap with the membership value zero. These values will be calculated depending on Δmin, Δmid, Δmax and the fuzzy factor, the parameter to tune the overlap.

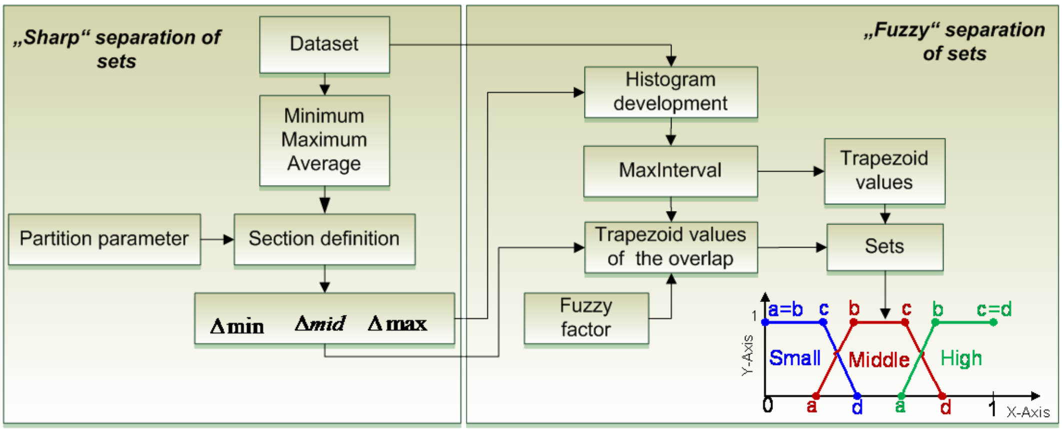

Figure 2-2: Function "Estimator" – function to calculate the adaptive fuzzy sets for the input variables

Rules. Important aspects for the calculation are the compositions of the fuzzy rules. In Table 2-1 four characteristic rules for computing the transition are shown. As mentioned before for curvy road segments the values of gripforce and steering moment were logical combined as an "AND" function because the driver shows two activities on curvy road segments. The rules were built in dependency to the current automation level and the road segments (straight, curve). This separation ensures the transition to be more intuitive.

Composition	Gripforce	Steering moment	Acceleration throttle	Brake pedal	Output
"AND"	Small	Small	-	-	Partly Automated
"AND"	Small	Middle	-	-	Neutral
"AND"	Middle	High	-	-	Driver Only
"AND"	High	High	-	-	Driver Only

Table 2-1: Four rules of 35 which take effect in the automation grade "Partly Automated" in curves

Driver adaptation. Driver adaptation is achieved by offline learning. Figure 2-3 shows the structure of the offline training. Thereby the left side of the figure illustrates the separation of the linguistic variable lateral acceleration into "small" and "high". After this separation the learning process starts in which the mentioned linguistic variables are collected for 90 seconds for a period with small and a period with high lateral acceleration each. These two data sets are delivered to the function "Estimator" (see Figure 2-2) to calculate the parameters a, b, c and d of the trapezoids for each set "small", "middle" and "high" of the four linguistic variables. Now the training is finished and the driver specific values are saved as sets.

Situation adaptation. After calculating and saving the driver specific data it is required to adapt the driver specific data to different road segments (straight, curve). Firstly, the fuzzy sets are adapted by a linear interpolation between the two recorded sets (small, high). The idea is that the linguistic variables increase linear with the lateral acceleration. Secondly, the fuzzy rules change depending on the road segment. In Figure 2-3 the final structure of the adaptive approach is summarized and combines the previous concepts.

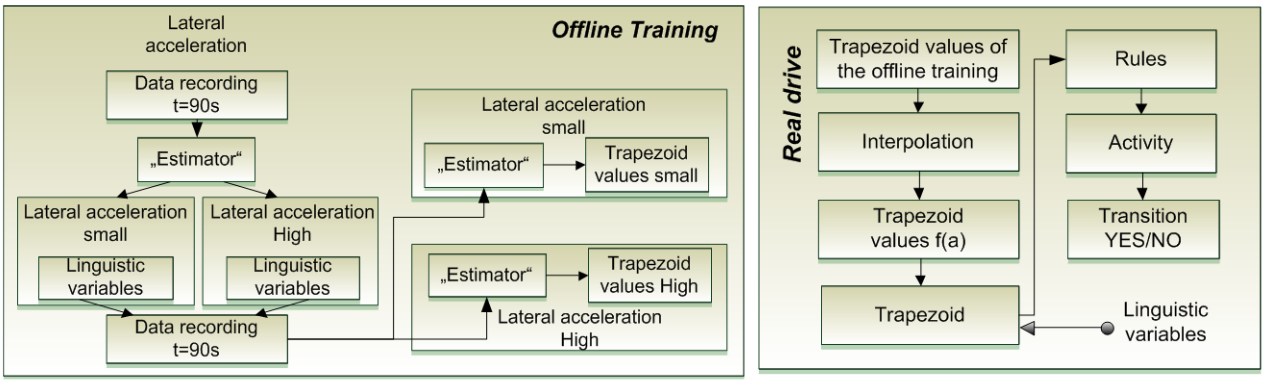

Figure 2-3: Left: Structure of the offline training, Right: Procedure after the training

Usability study: Results and Discussion

Study design

For the usability study an inner city circuit was used to validate the driver intention models from the previous section. The circuit includes different curves (radius of 30 m, 60 m and 90 m), straight road segments and especially forks to cover the most possible situations in a lane following scenario. The usability study was carried out in a fixed base simulator at DLR. Additionally, a sidestick was used instead of a steering wheel, acceleration throttle and brake pedal because of a precise grip force sensor. This made sure that no noise due to imprecise sensors impaired the validation of the models. Moreover the study design included a longer phase of simulator training to get the driver used to the sidestick as seen in Figure 2-4. This was followed by a naive training of the automation levels to ensure that drivers understand driving with a vehicle with two different automation levels. All together this guaranteed a correct validation of the models and their performance.

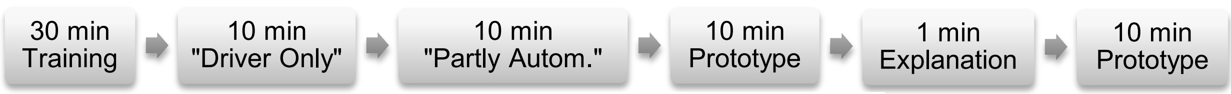

Figure 2-4: Timing of the usability study

In the usability study a between-subject design was realized. Group A used the prototype with the adaptive model, called prototype “Adap” in the following. Group B used the non-adaptive model, called prototype “Non-Adap” in the following. Within group A six subjects participated (five male, one female, age range 22- 27, average age 25). In group B seven subjects participated (six male, one female, age range, 21-46, average age 29).

Comparison

Transitions. Subjects were first asked to rate the transitions between the two automations levels “Driver Only” and “Partly Automated”. Since transitions are depending on the driver intention model this gives a clear feedback about the implemented model. As in Table 2-2 shown the adaptive prototype showed better performance. Most of the subjects felt the transitions to be accurate. Furthermore, subjects described the transitions as quite reliable, quite controllable and quite comprehensible in the median. The ratings are also very dense about the median and positive. For the non-adaptive prototype subject ratings show a larger spread and contain some outliers to the negative.

The transitions were…	Prototype	-3	-2	-1	0	1	2	3	
too early	Adap			1	21	2			too late
	Non-Adap		1	3	9			1	
unreliable	Adap			1		3	14	6	reliable
	Non-Adap		1	1	3	4	2	3	
incomprehensible	Adap					4	11	9	comprehensible
	Non-Adap		2			4	5	2	

Table 2-2: Subject rating of the transitions: For both prototypes both directions were rated separately but are shown in one table. For “Adap”-prototype additional a distinction between curve and straight segments was made, therefore more ratings were available

Activity display. The system transparency as one requirement for the non-adaptive model mentioned in the introduction is achieved by a visual display, called activity display (see Figure 2-1 (right)). Table 2-3 shows the subject ratings of the activity display. The activity display improved the understanding, comprehension and the controllability of the transitions for both prototypes. Also driving in general was rated to be better with the display. Compared to each other the advantage of the display was slightly better for the non-adaptive prototype. One reason seemed to be the intuition. A higher number of subjects using the adaptive prototype had to look less frequently to the display than subjects using the non-adaptive prototype. Furthermore a higher number of subjects wouldn’t have needed the display to get along with the automation. These two results point out that the adaptive prototype is more intuitive. This is in fact one goal of partly automated vehicles and underlines the benefit.

The activity display helped to improve the…	Prototype	-2	-1	0	1	2
understanding of the automation	Adap		1	1	1	3
	Non-Adap			1	1	5
comprehension of the automation	Adap			1	2	3
	Non-Adap				2	5
controllability of the automation	Adap			2		4
	Non-Adap			1		6
driving in general	Adap		1	1	1	3
	Non-Adap			2	2	3
I had to look frequently to the activity display	Adap	2		3	1	
	Non-Adap	1		2	2	2
I wouldn’t have needed the activity display	Adap		3	1	1	1
	Non-Adap	4	2		1	

Table 2-3: Subject rating of the activity display: -2/2 means totally incorrect/correct, -1/1 means quite incorrect/correct, 0 is neutral

Overall evaluation. Table 2-4 shows the overall evaluation of the two prototypes. The adaptive prototype shows the greatest values. Especially the learnability, the usability and the comfort are evaluated very high. On the other hand, the non-adaptive prototype is evaluated more negatively with regard to the before mentioned characteristics. The benefit of the adaptive prototype is also shown in the last two characteristics. The adaptive prototype is evaluated as more useful and more pleasant. So far the benefit was more obvious than the necessity of an adaptive approach. By looking at the overall ratings for the non-adaptive prototype the necessity becomes clear. The ratings are only rather good with negative outliers whereas as the results for the adaptive prototype are quite good to very good with no negative outliers.

The prototype was…	Prototype	-3	-2	-1	0	1	2	3	
bad	Adap						4	2	good
	Non-Adap					3	1	2	
uncomfortable	Adap						3	3	comfortable
	Non-Adap		1	1	1		3	1	
difficult to learn	Adap						1	5	easy to learn
	Non-Adap		1			1	4	1	
difficult to use	Adap						1	5	easy to use
	Non-Adap		1		1	2	2	1	
useless	Adap					1	2	3	usefull
	Non-Adap					4	2	1	
annoying	Adap					2	2	2	pleasant
	Non-Adap			1	2	1	2	1	

Table 2-4: Overall evaluation of the prototypes

Conclusion and Perspective

The paper analysed driver intention models in context of partly automated vehicles and a conflict prevention strategy. Therefore two models, a driver and situation adaptive model and a model based on an average driver were implemented. Thereby the driver and situation adaptation was achieved by using fuzzy logic with adaptive fuzzy sets and rules. The fuzzy sets were trained offline during 90 seconds, which is quite short. The benefit and necessity of the adaptive intention model compared with the non-adaptive model could be shown. Even though the learnability of the non-adaptive model was quite easy for nearly all subjects through the activity display. This was not sufficient. The model had to be adaptive to obtain very good results. In the next step the conflict detection will be further improved. The goal is to extend the conflict detection by classifying the reason for the conflict. By knowing the reason for the conflict this allows to adapt the automation behaviour on the manoeuvre and/or trajectory level to the driver. This would be another strategy of conflict prevention. The advantage would be to reduce the number of transitions and thus to increase the acceptance on partly automated vehicles. Therefore an observer model will be implemented to learn the driver behaviour.

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