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PERSONALIZATION OF ACC STOP AND GO TASK BASED ON HUMAN DRIVER BEHAVIOUR ANALYSIS

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Abstract: Intelligent vehicle systems have introduced the necessity for the designer to take care of user preferences in order to make as comfortable as possible several kinds of driving features. This requirement originates the problem of a suitable analysis of the human performances to be implemented in automatic driving tasks. The aim of this paper is to personalize an Adaptive Cruise Control with Stop and Go features (ACC/S&G) for a urban scenery. This can be accomplished by taking into account the driver behaviour characteristics evaluated by means of a statistical analysis performed on data collected, for a set of drivers, during a common urban journey. It will be shown that the personalization of the ACC/S&G task can be obtained by a suitable tuning of the parameters of a reference generator without modifying preexistent control algorithms structure. *Copyright© 2002 IFAC*

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1. INTRODUCTION

The recent developments on intelligent vehicle systems have introduced the necessity for the designer of such systems to take care of user preferences, in order to make as comfortable as possible these driving features. Thus, the problem of implementing several automatic driving tasks, taking into account driver characteristics by suitably modelling the human performances, has been widely studied in the last years. For example, in Joannou and Chien (1993), following the idea introduced in Burnham *et al.* (1974), an intelligent cruise control strategy has been proposed using and comparing different dynamical models to describe driver behaviours. Moreover in Borodani *et al.* (1998) a robotized gearbox has been designed optimising its comfort features on the basis of estimated driver characteristics. Then, in Fancher *et al.* (2000), a forward collision warning system has been introduced combining concepts from vehicle dynamics, control theory and human factors psychology. Furthermore, different studies on driving behaviour modelling have been developed by means of learning mental models, (see e.g. Rasmussen, 1983; König *et al.*, 1994; Goodrich and Boer, 1998). The framework in which this work has been developed is an Adaptive Cruise Control (ACC) with Stop and Go features (ACC/S&G) for a urban scenery. In this context, one of the main requirements is the possibility of tuning the control strategy according to the driving style. In order to accomplish this task, a study by means of statistical analysis methodologies on twenty different drivers has been carried on, to give evidence to their behaviour during the driving. In the related literature, other approaches have been considered to solve similar problems. In particular, in Wewerinke (1996), the overtaking task is analyzed by using both system theoretic and neural networks approaches to model human operators behaviour. As a matter of fact neural networks methodologies have been widely used to describe and to adapt human behaviours in different driving tasks (see e.g. Nechyba and Xu, 1996). Moreover, in Goodrich and Boer (1998), a membership function methodology is used to describe human behaviours in "cut in" situations. In this paper we show how it is possible to determine and classify the driver behaviour, which acquired signals are suitable for this task, which parameters can be used to describe the driving style and how they can be taken into account by the vehicle control system.

2. ACC/S&G PROBLEM DESCRIPTION

The controlled vehicle moves in a urban scenery, either strictly following, along the lane, the preceding vehicles at a target relative distance $\overline{d}_R$, depending on vehicle speed, or at a target velocity $\overline{v}_F$ in absence of a preceding vehicle. According to the preceding traffic conditions, the controlled vehicle has to accelerate or decelerate and even to stop automatically, keeping safety distance. Acceleration and deceleration are constrained by safety, comfort and mechanical bounds, but inside these constraints they have also to depend on the usual driver behaviour: when using the ACC/S&G, quiet or aggressive drivers need to feel the same sensations they are used to in manual driving. To this aim, differences in driving behaviour have to be described by simple parameters, detected from the usual signals acquired for the ACC task and used as directly as possible in control algorithms. The considered control structure is depicted in Figure 1 where the two blocks named "Vehicle" and "Vehicle and Radar sensors" represent the physical system, while the other three blocks represent the control architecture; the signals in Figure 1 will be described in details in Section 3. One of the objectives of the ACC

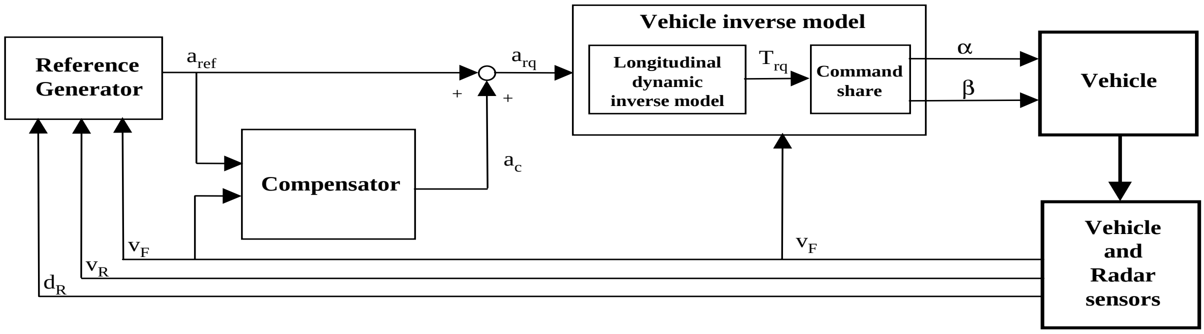

Fig. 1. Control structure.

personalization was to modify the control algorithms as less as possible in order to keep the ones adopted for the non personalized version of the same task. In fact, personalization can be obtained by means of a suitable design of the Reference Generator block only, whose structure will be discussed in details in Section 6. This block can be regarded as an approximated model of the human driver and its aim is to generate, on the basis of the on line acquired vehicle and environment data, an acceleration profile a_{ref} in agreement with safety, comfort and personalization requirements. In general (see, for example, Burnham *et al.*, 1974; Joannou and Chien, 1993) a_{ref} is a function $f(\cdot)$ of the relative speed v_R and the relative distance d_R with respect to the preceding vehicle and of the controlled vehicle speed v_F (i.e $a_{ref} = f(v_R, d_R, v_F)$). In Section 6, it will be shown how the relation $a_{ref} = f(v_R, d_R, v_F)$ can be "defined" and used to personalize the ACC/S&G task. The other blocks in Figure 1 are not interested by the personalization and they will not considered in this paper, except for the brief description that follows. The "Compensator" block is essentially made up by a Proportional plus Integral algorithm used to compensate the error between the reference vehicle speed $v_{ref} = \int a_{ref}$ and the measured vehicle speed v_F. The "Vehicle inverse model" generates the throttle opening angle α or brake circuit pressure β needed by the requested acceleration a_{rq}, through the requested torque T_{rq}; note that this block takes into account the main non linearities of the vehicle.

3. EXPERIMENTAL SETUP

A FIAT Brava 1.6 car was equipped with obstacle detection radar sensor, vehicle sensors and real time data acquisition system to perform the field experiments and observations. It was used on a test urban track lasting one hour, with traffic lights requiring multiple Stop and Go manoeuvres. According to this set up, the following acquired variables have been chosen as indicative and/or discriminating of driving styles:

(1) relative distance and relative speed between the considered vehicle and the preceding one denoted respectively by d_R and v_R;
(2) throttle opening angle denoted by α;
(3) brake circuit pressure denoted by β;
(4) controlled vehicle speed denoted by v_F.

Few comments are due to explain this choice. Variables related to point 1 are representative of the environment surrounding the driver, so they symbolise the causes that produce different "human" reactions such as braking or accelerating. On the other side, variables related to points 2 and 3 represent the way the driver actuates her/his reactions to the external stimuli. Another interesting aspect regarding α and β is the fact that they represent the commands generated by the control algorithm. All the signals mentioned in points 1 to 4 are got, as explained, by direct measurements from the on board instrumentation. Other variables obtained by the ones just mentioned may be defined. In particular, the headway time $T_H = \frac{d_R}{v_F}$ and collision time $T_C = \frac{d_R}{v_R}$ will be considered. In fact variables T_H and T_C (together with v_F) were shown to be the more directly perceived by drivers (Lee, 1976). Then, a set of tests oriented to the extraction of the driver features in ACC/S&G scenery has been defined. Common to all the tests is the settlement of a urban journey in which each driver was subject to some driving constraints such as lane and queue keeping without overtaking. During the journey all the variables considered (points 1 to 4) have been recorded and single Stop and Go tracts (the typical acquired signals of such tracts are depicted in Figure 2) were extracted by selecting single nonzero v_F sequences. Inside each of these sequences, single nonzero α and β sequences were further isolated. In order to distinguish different situations inside a single S&G sequence we may divide it into three main phases:

GO corresponding to the transient required to approach the subsequent CRUISE / TRACK phase; note that no distance tracking is possible, in this phase, due to its transient characteristics.

CRUISE / TRACK corresponding to the situation in which the vehicle is performing a constant speed following, in absence of a preceding vehicle, or a relative distance following, in presence of the preceding vehicle, respectively.

STOP corresponding to the situation requiring a deceleration leading to stop the vehicle.

On the basis of those latter sequences the driver characteristics discriminating analysis has been performed.

4. DRIVING STYLE ANALYSIS

In order to stress possible differences in driving behaviour, a preliminary analysis has been carried out by

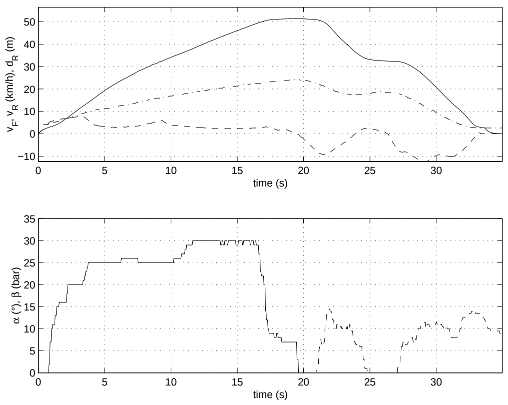

Fig. 2. Acquired signals. Above: v_F (km/h) solid, v_R (km/h) dashed, d_R (m) dash-dotted. Below: α (°) solid, β (bar) dashed.

means of a reduced set of drivers, whose driving characteristics were evidently in contrast. One subject (a test driver) was requested to drive in a very aggressive manner, while the others drove normally or quietly. From this analysis it was possible to conclude that the drivers were well distinguishable during the GO and TRACK phases but no significant differences were put in evidence in STOP phase (Canale *et al.*, 2001). Then, on the basis of a 20 subjects set acquired sequences, a more systematic statistical analysis was carried out in order to classify these sequences in a limited number of groups, at most three or four, each one corresponding to a driving style. To this aim, the sequences have been considered as completely independent each other, i.e. as any of them has been originated by a different driver, to enlarge as much as possible the number of "samples" to be analyzed. Then, on the basis of these samples, a cluster analysis (see e.g. Anderberg, 1973) has been worked out for each one of the previously defined GO, TRACK and STOP phases. It has to be noted that with this procedure, the two problems of identifying different driving styles and assigning a given driver to a cluster can be afforded separately. As it will be shown in Section 6 the ACC S&G task personalization can be obtained by considering the driving style analysis problem only.

GO phase cluster analysis. The aim of this analysis is to study the way the driver activates an acceleration procedure after a STOP phase. To this end, we observe that the shape of the selected α signals inside a S&G tract is nearly trapezoidal (see Figure 2). Therefore, for each α sequence corresponding to a GO phase, the slope s_α of the best interpolating line, in the least square sense, has been computed starting from the first sample of the sequence until the last sample for which the behaviour is non decreasing. Moreover the maximum value M_α of the considered α sequence has been computed too. This way, the cluster analysis of the GO phase gave rise to four clusters whose characteristics are pointed out in Table 1, where $\mu(\cdot)$ is the mean value and $\sigma(\cdot)$ is the standard deviation.

TRACK phase cluster analysis. The TRACK sequences have been selected considering those S&G subtracts for which it results $v_F \geq 20$ km/h and $-5 \leq v_R \leq 5$ km/h for a period longer than 5 s. For such isolated TRACK sequences, the headway time T_H and its standard deviation inside the considered tract σ_{T_H} have been considered as indicative variables. Given this setup, three clusters have been generated whose characteristics are given in Table 2 in which, as before, $\mu(\cdot)$ and $\sigma(\cdot)$ represent the mean value and the standard deviation respectively.

STOP phase cluster analysis. The aim of this analysis is to study the way the driver activates a deceleration manoeuvre to stop the vehicle. We may observe that, as α, also β signal has a nearly trapezoidal shape (see Figure 2). Therefore also for each β sequence the slope s_β and the maximum value M_β have been computed according to the same procedure followed for α. Moreover, in order to investigate the "environmental" setup that causes the driver decision to activate a braking manoeuvre we have also considered the values of signals v_R and T_H "frozen" at the time instant when the brake has been activated. Then, by using the above mentioned parameters three clusters have been generated, whose characteristics are pointed out in Table 3, where again $\mu(\cdot)$ is the mean value and $\sigma(\cdot)$ is the standard deviation.

As a matter of fact, the CRUISE phase is a typical driving modality for non urban scenarios. Then, it results quite difficult to test such modality in the considered urban setting. Anyway, the CRUISE phase can be seen as a speed regulation problem, almost not influenced by preceding traffic. In this case the only driver's dependent characteristic is the transient period before reaching the steady state speed value that may be considered as a GO phase.

From the presented analysis it can be already pointed out that, in each phase, the generated clusters are well distinguishable. For example, from Table 1 it can be seen that the four clusters have different $\mu(s_\alpha)$ and clusters 1 – 2 differ from clusters 3 – 4 for $\mu(M_\alpha)$. Similar considerations can be made for the values presented in Tables 2 and 3 (see for further details Canale and Malan, 2002).

In the next Section, some criteria to classify and assign a driver to a predetermined cluster will be given.

5. DRIVER CLASSIFICATION

Once the clusters corresponding to each S&G phase have been generated, the problem we have to face consists in finding some suitable criterion in order to assign a driver to one of such clusters. The driver assignment procedure that has been worked out can be summarized as follows:

Step 1 Acquisition of driver's data according to the criteria outlined in Section 3.
Step 2 Separation of single S&G sequences.
Step 3 Assignment of every single sequence to a predefined cluster.
Step 4 Computation of the membership percentage of the sequences to the clusters.
Step 5 Driver assignment on the basis of the greater membership percentage of the sequences to a cluster.

Table 1. GO phase Cluster Analysis Results

Cluster	# of samples	$\mu(s_\alpha)$ $(\circ/s)$	$\sigma(s_\alpha)$ $(\circ/s)$	$\mu(M_\alpha)$ $(\circ)$	$\sigma(M_\alpha)$ $(\circ/s)$
1	254	27.18	8.34	29.92	8.89
2	253	59.58	23.72	36.67	9.89
3	41	70.07	28.12	77.68	9.31
4	10	216.99	45.77	77.10	13.33

Table 2. TRACK phase Cluster Analysis Results

Cluster	# of samples	$\mu(T_H)$ (s)	$\sigma(T_H)$ (s)	$\mu\left(\sigma_{T_H}\right)$ (s)	$\sigma\left(\sigma_{T_H}\right)$ (s)
1	132	1.62	0.20	0.12	0.05
2	135	1.33	0.23	0.30	0.06
3	104	1.06	0.15	0.19	0.06

Table 3. STOP phase Cluster Analysis Results

Cluster	# of samples	$\mu\left(s_\beta\right)$ (bar/s)	$\sigma\left(s_\beta\right)$ (bar/s)	$\mu\left(M_\beta\right)$ (bar)	$\sigma\left(M_\beta\right)$ (bar)	$\mu(v_R)$ (km/h)	$\sigma(v_R)$ (km/h)	$\mu(T_H)$ (s)	$\sigma(T_H)$ (s)
1	166	19.27	9.58	14.05	3.40	-3.92	2.50	1.28	0.38
2	164	23.31	12.42	13.77	4.31	-13.24	8.87	2.78	1.08
3	51	38.60	31.61	24.55	6.01	-6.48	4.18	1.43	0.63

The cluster assignment problem of each sequence, considered in Step 3, has been performed using and comparing two different procedures. The first one uses the standard routine `classify` of MatLab Statistics Toolbox based on the computation of the Mahalanobis distance (The MathWorks, 1999) and on the consequent assignment on the basis of the lowest distance. The second one relies on the so called "*k* - Nearest Neighbour" (*k*NN) technique (see e.g. Fukunaga, 1972) which requires the computation of the distance (e.g. Mahalanobis) of the sample to assign from *every* individual sample used for the cluster generation. Successively the k nearest samples from the sample to assign are selected (usually k is of the order of some unity and it represents a tuning parameter of the algorithm). The parameter k satisfies the relation $k = \sum_{i=1}^{N} k_i$, where k_i is the number of the k selected samples belonging to the i^{th} cluster and N is the total number of clusters. The assignment of the sample to a cluster is then done on the basis of the largest k_i. The driver membership to a cluster is therefore settled on the basis of the greater percentage of sequences belonging to every generated cluster.

The proposed assignment procedure has been applied to three new drivers. In Tables 4, 5 and 6 the cluster membership percentage computed by using both `classify` and *k*NN algorithms are reported for each of the S&G phase for the three new drivers. The *k*NN algorithm was tested with the parameter k varying between 1 and 10 and no substantial differences in the obtained results were noted (results in Tables 4, 5 and 6 are obtained fixing $k = 5$). In these Tables, the boldface numbers put in evidence, on the basis of the largest percentage, the cluster the considered driver has been assigned to.

Table 4. Assignment percentages of new drivers for GO phase.

Algorithm	`classify`				*k*NN			
Cluster	1	2	3	4	1	2	3	4
Driver #1	**52**	48	0	0	**59**	41	0	0
Driver #2	**78**	22	0	0	**84**	16	0	0
Driver #3	28	**72**	0	0	40	**60**	0	0

Table 5. Assignment percentages of new drivers for TRACK phase.

Algorithm	`classify`			*k*NN		
Cluster	1	2	3	1	2	3
Driver #1	**47**	**47**	6	**47**	**47**	6
Driver #2	**77**	15	8	**77**	15	8
Driver #3	13	20	**67**	13	20	**67**

Table 6. Assignment percentages of new drivers (STOP phase).

Algorithm	`classify`			*k*NN		
Cluster	1	2	3	1	2	3
Driver #1	17	**72**	11	**56**	33	11
Driver #2	13	**74**	13	35	**56**	9
Driver #3	31	13	**56**	**44**	19	37

As it can be noted from the presented results, the assignment of every driver takes place in a univocal way, independently from the used algorithm, for the GO and TRACK phases. As a matter of fact, the assignment of Driver #1 presents an ambiguous situation in the TRACK phase. This problem may be solved by increasing the number of the acquired sequences, as it will be discussed later. On the other hand, in STOP phase discordant results have been obtained. This fact appears quite reasonable as, in typical urban journeys, the braking manoeuvres are mainly influenced by the (intense) traffic flow than by the driving style.

Some indications concerning the minimum number of sequences to acquire to assign a driver are due. Presented results are obtained considering, for each driver, a sequence number of about 25 for GO phase, 15 for TRACK phase and 20 for STOP phase. It sounds reasonable to suppose that such sequence numbers may suffice to assign a driver. This number should be increased for those drivers presenting doubtful assignment (see e.g. Driver #1 in Table 5). In the next Section the Reference Generator and its personalization, according to the driver behaviour analysis results, will be described.

6. REFERENCE GENERATOR PERSONALIZATION

The problem of the reference generation plays a key role for the longitudinal vehicle control in the

ACC/S&G driving task. In principle, the acceleration profile must be generated taking into account safety and comfort of the required driving manoeuvres but also driver personalization features can be considered too. Moreover, it appears reasonable to differentiate the reference generation according to the Stop and Go phases outlined in Section 3. The switching among the three different phases is handled by a supervision logic, here not described, that, on the basis of the acquired signals, enables the correct generation procedure.

GO Considering this phase, the reference generation structure of Figure 3 can be suitably exploited. As it

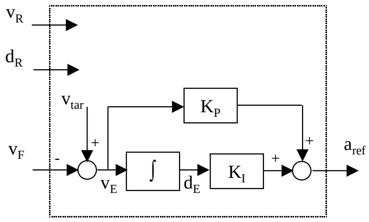

Fig. 3. GO and CRUISE phases reference generator.

can be seen, only the measured signal v_F is used for the reference generation while the other two acquired signals d_R and v_R are only considered for switching logic purposes. This scheme can be actually personalized taking into account the mean value $\mu(s_\alpha)$ of parameter s_α (see Table 1) related to the GO cluster which the considered driver has been assigned to. The required acceleration profile a_{ref} can then be obtained by fixing the reference generator "internal" input as $v_{tar} = v_F^\alpha$ where v_F^α is the vehicle speed obtained by applying to the vehicle a ramp throttle signal α with the considered slope $\mu(s_\alpha)$. Note that, given the driver characteristics, signal v_F^α can be precomputed and stored. This way, the reference generation for the GO phase forces the vehicle longitudinal control to follow the personalized speed reference v_{tar} until the TRACK phase is reached. The parameters K_P and K_I can be tuned taking into account the comfort characteristics of the acceleration profile. To this end, let us consider the scheme depicted in Figure 4. This scheme can be regarded as a reasonable linear approximation of the real behaviour of the controlled longitudinal vehicle dynamics. Coefficient $\eta < 1$ represents, as a first approximation, the rate of the speed that has been really rendered to the vehicle, detracted the friction losses and aerodynamic effects. The transfer function

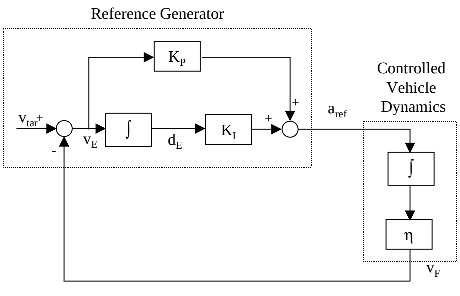

Fig. 4. Approximated controlled longitudinal vehicle dynamics and reference generation scheme.

$G_{ref}(s)$ between the input v_{tar} and the output of the reference generator a_{ref} is given by:

$$G_{ref}(s) = \eta s \frac{K_P s + K_I}{s^2 + K_P s + K_I} \tag{1}$$

Then, in order to obtain the smoothest and the fastest acceleration profile, the poles of the transfer function (1) have to coincide. This can be obtained by posing $K_I = \frac{K_P^2}{4}$. The value of K_P may be chosen to tune the response speed of a_{ref}. Typical values for K_P range from 0.5 to 0.7 s^{-1}.

CRUISE All the reasoning made for the GO phase are still valid with the only difference that, after the GO phase transient, v_{tar} is set to a constant value selected by the driver according to the speed limitation: $v_{tar} \leq$ 70 km/h.

TRACK This phase is characterized by the tracking of the target distance d_S:

$$d_S = s_0 + T_H \cdot v_F \tag{2}$$

where T_H is the headway time, v_F is the vehicle speed and s_0 can be regarded as a fixed safety distance. In this case the reference generation structure showed in Figure 5 may be adopted.

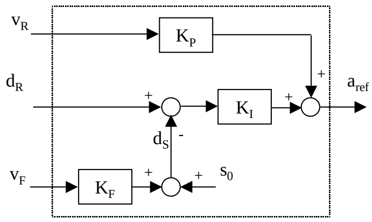

Fig. 5. TRACK phase reference generator.

Now, considering the scheme in Figure 5 and equation (2), the most natural way to personalize this feature is to set $K_F = \mu(T_H)$, where $\mu(T_H)$ is the mean value of T_H of the TRACK cluster which the driver has been assigned to (see Table 2). The values of K_P and K_I may be computed in order to ensure comfort characteristics to the generated acceleration profile by following similar criteria as done in the GO and the CRUISE phases.

STOP During this phase a deceleration is required whose intensity depends on the way the preceding vehicle is going to be approached or, in other words, to the level of emergency induced by the approaching manoeuvre. The smoothness characteristics of the acceleration profiles generated by both the schemes in Figure 3 and 5 may not suffice to avoid collision in dangerous situations. Consequently, a purely kinematics approach of the form:

$$a_{ref} = \gamma \cdot \frac{v_R^2}{2(d_R - d_S)} \tag{3}$$

can be adopted, where $\gamma = \gamma(T_C) \geq 1$ is a coefficient measuring of the emergency level required by the braking manoeuvre (Persson *et al.*, 1999) and $\underline{d}_S$ is a fixed stop distance. As it results from the statistical analysis described in Section 4, it is not possible to put in evidence significant differences among drivers during this phase. For this reason equation (3) is used to generate a_{ref} by setting $\bar{d_S}$ to a fixed value, not depending on the driving style.

In order to show the effectiveness of the proposed driver assignment and reference generation procedures, we have simulated the controlled vehicle dynamics supposing that the speed of the preceding vehicle was made up by the real acquired speed profiles $v_L = v_F + v_R$. Then, the simulated variables have been compared with the corresponding real recorded ones. The advantages of the personalization can be shown by computing the rms error between the simulated variables and the measured ones. In particular, the rms errors of the vehicle speed v_F and of the relative distance d_R related to the TRACK phase have been computed for every sequence of each driver considered in Section 4. This computation was carried on using the personalized parameters of the "GO" reference generator set to the value corresponding to the cluster the driver has been assigned to and fixing the personalized parameters of the "TRACK" reference generator to the different values of the three clusters. In Tables 7 and 8 the mean values of the rms errors e_{v_F} and e_{d_R} between the simulated variables and the measured ones computed considering all the sequences for a given driver are reported respectively. It can be seen from the boldface values in Tables 7

Table 7. rms error e_{v_F} (km/h).

TRACK Cluster	1	2	3
Driver #1	**3.04**	**3.05**	3.25
Driver #2	**2.80**	2.96	3.10
Driver #3	3.34	2.92	**2.60**

Table 8. rms error e_{d_R} (m).

TRACK Cluster	1	2	3
Driver #1	**3.09**	**3.02**	3.24
Driver #2	**2.70**	3.23	3.80
Driver #3	6.18	4.48	**3.07**

and 8 and considering Table 5 that the lower values of the rms errors are obtained when the considered personalized reference generator parameters are set to the values corresponding to the cluster the driver has been assigned to. It can also be noted that for the Driver # 1 there is only a slight difference between the considered rms errors obtained by considering the personalization parameters of TRACK cluster 1 and 2. This fact sounds reasonable comparing this results with the TRACK phase assignment data for Driver #1 presented in Table 5.

7. CONCLUSIONS

The problem of suitably modelling the human performances to be implemented in automatic driving tasks has been afforded in order to personalize an Adaptive Cruise Control with Stop and Go features for a urban scenery. To this aim, the possibility to distinguish different driving styles has been demonstrated by taking into account the driver behaviour characteristics. These latter have been evaluated by means of a statistical analysis performed on data collected, for a set of drivers, during a common urban journey. Moreover a driver assignment procedure has been introduced to classify the driving behaviour upon the features defined by the predetermined cluster. At last, it has been shown that the personalization of the ACC/S&G task can be effectively obtained by a suitable tuning of the parameters of a reference generator without modifying preexistent control strategy.

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