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PREDICTION OF DRIVER'S WORKLOAD BY MEANS OF FUZZY TECHNIQUES

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Abstract. The driver, through sight, acquires a lot of information from the road environment, most of which is necessary for his safe route. However, if the amount of information per unit of time is excessive, potentially dangerous situations of overload could be created. Even the opposite condition, that of a road that does not adequately stimulate the cognitive functions of the driver, may pose certain safety problems because it triggers the so-called boredom effect. This phenomenon, generally classified under the name of workload, was treated with great depth in literature but, probably, sufficiently detailed methodology has not yet been proposed for making forecasts on this variable along the road. The difficulty of preparing a reliable model can be explained by some of the characteristics of the road environment: many uncertain variables, including the human factor, choosing the most appropriate analytical method, lack of appropriate databases. The purpose of this article, therefore, is to present a prediction model based on the analysis of physiological workload by means of head-eyes movements and fuzzy techniques applied to a real context. The results obtained, although limited by the observed data set, allowed for the prediction with some accuracy of the tendency of the workload, referring also to the overload and under load thresholds position of which was defined on the basis of performance measurements along the road under consideration. In the first stage of the study the methodology is applied to the design of maintenance on an existing road, but once the correctness of the procedure is established, it can also be extended to new roads.

Keywords: road safety, road design, visual behaviour, mental workload, Fuzzy Logic, prediction analysis.

1. Introduction

Literature in recent years has proposed some definitions of workload but all of these are characterised by difficulties of quantification and, above all, of prevision especially because of the number of the variables involved.

Some authors (Zijlstra, Mulder 1989; Wickens 2002), with regard to road problems, have defined the mental workload as a simple difference between the cognitive demand received by the driving task and the skill of attention. De Waard *et al.* (2008) added that the workload cannot depend on the type of task that the driver must perform while driving but it is fundamental to determine the effects of these demands on the driver himself. With regard to this, the author has also found certain factors that influence the workload and that can be classified as dependent on the environmental context (traffic demands, vehicle ergonomics, automation and feedback) or, instead, on the nature of the driver (monotony, fatigue, sedative drugs, alcohol, experience, age and strategy) with a procedure similar to that used years before by Eggemeier *et al.* (1991).

More recently Brookhuis and De Waard (2010) carried out tests with a simulator identifying numerous variables that intervene in this phenomenon and concentrating their attention on thresholds (redlines) beyond which there are dangers of overload and under load.

Eggemeier *et al.* (1991) and Rubio *et al.* (2004) proposed a list of certain factors necessary to characterize the mental workload, such as Sensitivity, Diagnosticity, Selectivity, Intrusiveness, Reliability, Implementation Requirements and Subject Acceptability.

The quantification process requires the classification within the following categories:

- performance measurements: the increase in complexity of the driving activity will determine the increase in demands and a worsening of performance;
- subjective measures: the user himself assesses his own effort as though he had perceived it through the filling in the particular questionnaires;
- physiological measures: these are directly related to mental workload.

Finally, other authors (Green 2004; Guhe *et al.* 2005; Patten *et al.* 2006) examined the uncertain and stochastic nature of human factors.

During the physiological measurements, eye movements represent one of the most popular methods and will

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also be used in this research. Moreover, the behaviour of the visual system has already allowed definition of important studies regarding the strategy of visual research, the selective attention and concentration time.

Yet, the results obtained do not offer a contribution that can be applied beyond the context in which the tests are conducted. In particular, this is the case because the indicators proposed do not keep a general validity (Djokic *et al.* 2010). Furthermore, the simulators, although allowing the definition of virtual scenarios in limit conditions that for reasons of safety could not be repeated with road tests, are still fairly detached from real conditions. Lastly, the numerous variables involved show uncertainties which are difficult to identify with traditional methods such as probabilistic analysis, thus, making invalid the possibility of predicting them in a designing phase (Makishita, Matsunaga 2008).

As a result, this study proposes a methodology that sets itself the goal of overcoming the above mentioned limits through recourse to clustering techniques that have been preparatory to the definition of a fuzzy model with which the analysis of forecast has been carried out. Clustering techniques (Sarimveis *et al.* 2003) applied to the database of origin, aimed to measure in the most objective way the membership functions and the rules of fuzzy model, always considered to be the weak link of these procedures due to the highly subjective contribution of the analyst.

The ultimate goal will be to use the fuzzy model to predict the main visual features based on environmental context and thus to assess the potential criticality of a number of design scenarios.

2. Method

As it is well known, the vision of the driver depends strongly on certain conditions beyond the road environment, such as the traffic, the level of natural light, the road signs and the geometric characteristics of the road and all these, in turn, influence the workload (Lewis–Evans *et al.* 2010). In order to examine any relationships between these sizes an equipped vehicle was provided (Fig. 1) able to record the ocular movements, the activities of the driver on the pedals and the main dynamic characteristics of the vehicle during motion. In particular, special equipment for tracking head/eye movements, consisting of three micro–cameras, plus a special hardware capable of recording most of the telemetry variables was installed on a 1600 cc Lancia Delta. The resulting video tapes were filtered and analysed with image analysis techniques, in order to extrapolate the head-eyes movements in correlation with the other parameters of the vehicle.

Before beginning the road trials 18 drivers were selected having filled a specific questionnaire regarding visual disparities, attitude, potential dangers, etc.

Certain simplifications were introduced in the deduction of ocular movements: since the subjects involved in the experimentation didn't suffer from strabismus, only the movement of one eye was considered. Moreover, the coordinate Y (vertical movements) was unimportant with regard to the coordinate X (horizontal movements) and was not considered. Yet, such characteristics were assessed for the automatic recognition of certain postures (glance towards the rear-view mirrors, the dashboard, etc.).

Testing was carried out on the road of about 7 km but it was only on the route of 1.5 km that it had features of consistency from the point of view of the route covered.

In order to further define the details of the instrumentation used, see the bibliography reported in this article (Antov *et al.* 2007; Bosurgi *et al.* 2007; Gonzales, Woods 2007).

The relationships between head–eye movements, road geometry and environmental context (De Waard *et al.* 2004; Pellegrino 2009; Zariņš 2006) allowed the determination of some interesting functions, such as:

– Context Information (CI): this characterizes the movement of the system head-eyes of the sample of users, under conditions of free flow, appropriately regulated through a sine function of regression. The assessment of the characteristics of the function (max, min and inflection points), compared to the road geometry, allow definition of the visual behaviour of the driver. For example, we have an inflection point when the user begins to interpret the following curve, looking at the internal edge. The max or the min of the function indicates that, instead, the driver has finished acquiring information and looks towards successive points of interest. For this reason (Fig. 2) we have called the distance between the inflection point and the max (or the min) as Length of Interpretation (LOI). The distance between the inflection and the beginning of the curve was called Available Length (AL) because it is the space in which the driver can acquire the necessary information before the curve begins. Lastly, the distance between the max (or the min) and the half curve is called Margin of Safety (MOS) because the greater this value, the sooner the user will manage to interpret correctly the bend. K is the amplitude of the sinusoid and is proportional with the driver's stress.

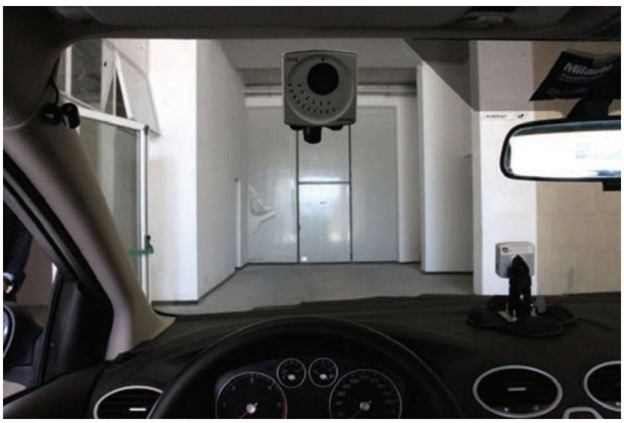

Fig. 1. Cockpit of the instrumented vehicle

– Visual Energy (VE): integration of the function CI allows quantification of the effort expended in visual interpretation; this can be referred to the single geometric element (for example a curve) or to an entire road.
– It is also interesting to refer the VE function to time (VE(t)). In this way the analyst may deduce information of a different type.

As mentioned in the Introduction section, researchers have always shown a great difficulty in quantifying the limits of the workload (de Waard *et al.* 2008) beyond which there could be situations of excessive fatigue or, on the contrary, of boredom or distraction. This problem is mainly due to the extreme variability of the sample of drivers with regard to the age, driving skill, experience, presence of pathologies that make the position of these bounds uncertain (Patten *et al.* 2006). With regard to this, in order to highlight these conditions of criticality, some researchers point rightly to the privilege measures of performance, such as the speed of the vehicle, the frequency of interrogation of the instrumentation on–board or of the rear-views, etc. (Horrey *et al.* 2009).

Instead, the choice by the author is the longitudinal deceleration beyond a certain limit ($at \geq 2$ m/s^2) and the control of the trajectory on a straight stretch for measurement, respectively, of the overload and of the under load. While it is deducible that excessive decelerations are symptoms of an uneasiness of overload, it is necessary to say a few more words for the criterion proposed by the under load. In fact, a state of boredom can manifest itself during the driving activity with trajectories that diverge from the axis of the driving lane with periodical trend. Of course, such measuring must be recorded far from bends where the user, almost always, deviates from the ideal axis of the lane in order to mitigate the effect of the transversal acceleration.

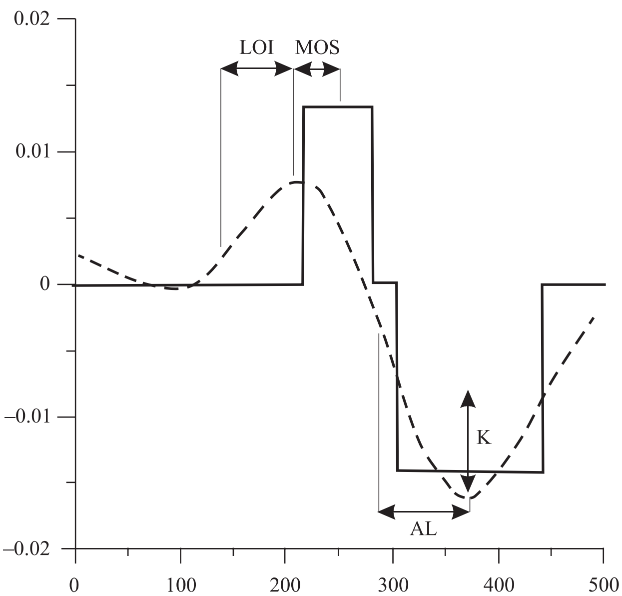

Fig. 2. Relationship between LOI, MOS, AL and K distances

2.1. The prediction model

The definition of a predictive model must be preceded by some preparatory steps. As stated, the problem of uncertainty was treated by fuzzy techniques.

This process is a form of multi–valued logic necessary to examine an approximate situation rather than a precise one. The variables involved can have a truth value between 0 and 1 and are not constrained to the only two truth values of binary logic.

In this regard, a membership function MF or $\mu A(x)$ defines the way in which the points of X in the input space are mapped to a membership value (or degree of membership) between 0 and 1. Fuzzy operators have to be considered the verbs of this technique and the "if-then-else" rules determine all the dependencies among the variables. At the beginning it will be necessary to fuzzify the input, computing the antecedent part of the rule (the if part); then, by means of the implication process, this result can be transferred to the consequent (then-else part of the rule).

Generally, fuzzy models can present some problems regarding the definition of membership functions and rules because of the excessive subjective role played by the analyst. This problem can be overcome through the use of clustering procedures, such as Subtractive clustering, fuzzy c-means, etc., applying them to the relevant data that will be so interpreted, organised and classified in an appropriate manner (Sarimveis *et al.* 2003).

More specifically, clustering techniques, as in this case, are used as pre-processors to determine and refine if-then fuzzy rules and membership functions. For example, Subtractive Clustering is an algorithm that estimates the number and centre of the clusters in a data set.

This technique (Chiu 1996) uses data points as candidates to the centre of the clusters, making the computation proportional to the size of the problem. Since each point can be the centre of the cluster, a density measurement for each x_i may be determined by the following expression:

$$D_i = \sum_{j=1}^{n} \exp\left[-\frac{\left\| x_i - x_j \right\|^2}{\left(\frac{r_a}{2} \right)} \right], \tag{1}$$

where r_a – a positive constant that represents a neighbourhood radius.

Therefore, a data point will have a high density value if it has a lot of neighbouring data points. The first centre of the cluster is chosen as the point which has the largest density value D_{C_1}. Therefore, the measurement of density or potential of each data point x_i is computed as:

$$D_i = D_i - D_{C_1} \times \exp\left[-\frac{\left\| x_i - x_j \right\|^2}{\left(\frac{r_b}{2} \right)^2} \right]. \tag{2}$$

where r_b (generally $1.5 \times r_a$) defines a neighbourhood radius that presents a decrement in its density. For these reasons, the data points near the first cluster centre X_{C_1} will have a reduced potential measurement. After calculating the density function, the next cluster centre will have the greatest density value. This procedure is finished after the sufficient number of clusters is attainted (Li *et al.* 1999).

For very small radii of clusters, there will be a greater number of membership functions and rules. Further rules can however be added, as in case of this paper, in order to better calibrate the relationships among the variables involved.

To acquire a complete data set and to cover the aim of the present research a survey on a rural road near the town of Messina (Italy) was arranged with an instrumented vehicle and a homogeneous sample of users. Some features are outlined below, and further details are specified in the references (Bosurgi *et al.* 2007; Pellegrino 2009).

The relief of visual behaviour and determination of the workload is not only the basis for building the predictive model, but also a benchmark for judging the results of the simulation. If these are deemed reliable, the tool can be used to predict the impact of different maintenance interventions on the workload of a particular class of users.

3. Results

Testing was characterised by an initial phase carried out on roads and a second one of data processing in the office. The movements of the head-eye system, requiring assessment with relation to the geometry of the road, present in the following figures the unit of measure in pixel transformed with an appropriate scale factor, through the simple operation:

$$\text{new coordinate} = (\text{old coordinate} - 150) / 2500 \quad (3)$$

As already stated in the previous paragraph, the movements of the system head-eyes of the entire sample were transformed through a function of sum of sine equations up to the fourth order:

$$a_1 \sin(b_1 x + c_1) + a_2 \sin(b_2 x + c_2) + a_3 \sin(b_3 x + c_3) + a_4 \sin(b_4 x + c_4) \quad (4)$$

with the following coefficients:

$a_1 = 0.4824$; $b_1 = 0.01844$; $c_1 = -0.662$;

$a_2 = 0.09653$; $b_2 = 0.03392$; $c_2 = 0.2931$;

$a_3 = 0.07995$; $b_3 = 0.05506$; $c_3 = -2.559$;

$a_4 = 0.2976$; $b_4 = 0.01515$; $c_4 = -6.986$.

The goodness of fit is summarised by means of these parameters: SSE – 1.529; R-square – 0.7136; adjusted R-square – 0.6602; MSE – 0.161

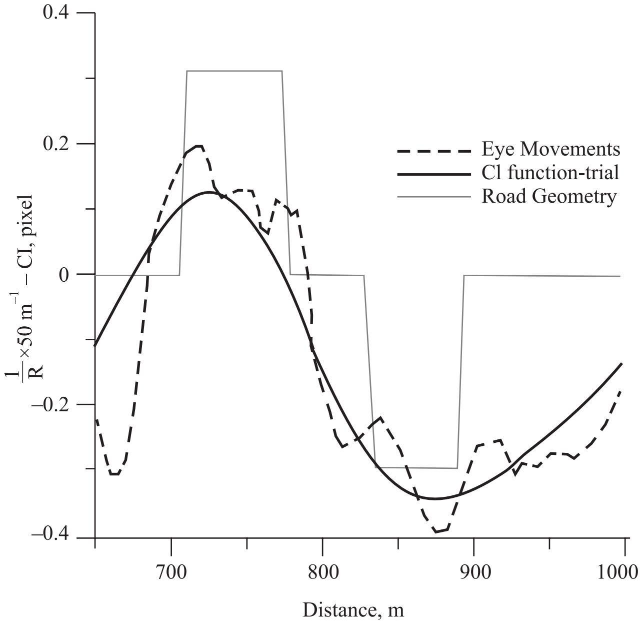

Fig. 3. Relationship among CI function, Head-Eye Movements and Road Geometry

Further analysis of this function allowed identification of the 1st and the 2nd order derivatives permitting identification of max, min and inflection points.

The study of CI function has allowed the author to verify if the visual behaviour of the sample is consistent with the mechanism of feedback and feed forward already presented in literature. To highlight this feature it is convenient to report the CI function in relation to road geometry. For example, in Fig. 3 the tendency of CI function representative of the behaviour of the drivers' sample is reported, recording of head-eyes movements of an individual user and horizontal road geometry.

As mentioned in the Method section, through the determination of the integral of the CI function, the Visual Energy function (VE) was extracted. This is representative of that aliquot of mental workload caused by road geometry (RG) but not by traffic.

The computation of the max, min and inflexion points, in relation to the road geometry (RG), permitted determination of the LOI, AL and MOS distance and, therefore, represent the behaviour of the drivers' sample.

Acceleration with regard to RG is reported in Fig. 4 and namely deceleration is assumed in this research as the index for controlling the overload threshold. The data emphasises that in the sections examined (250–400 and 650–1000) there are variations of a certain relevance only in the first bend (R = 70 m) but without that exceeded the allowable threshold ($a > 2$ m/s^2).

As already mentioned, such a variable cannot be used for the identification of a state of under load since the speed constancy (acceleration or deceleration near to zero) doesn't always lead to a state of boredom or potential carelessness of the driver.

For this reason the transversal position of the vehicle has been measured in respect to the lane axis along a straight stretch without noting an evident decline in drivers' performance. Analysis of Fig. 5 highlights that the trajectory followed by the vehicle detaches itself from the axis only for contained deviations during an interval of 20 cm; these can be considered to be absolutely normal and, therefore, do not indicate distraction or boredom by the user.

Of course in a bend this information makes no sense, since the driver hardly follows the axis of the lane as it tends to shorten the distance travelled.

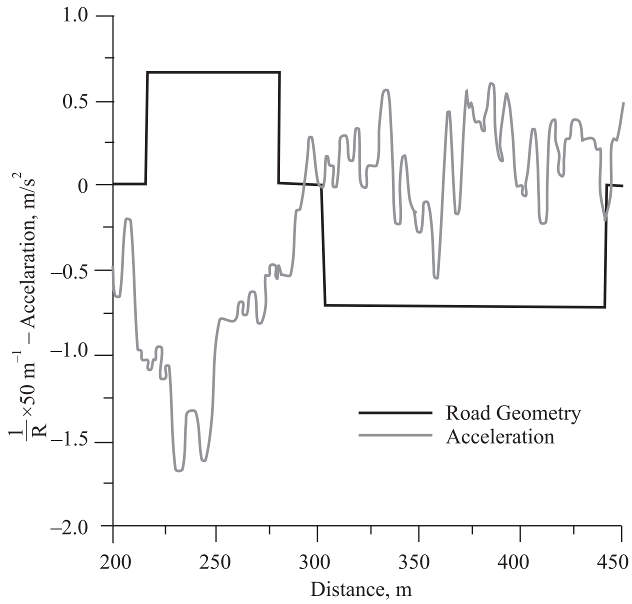

Fig. 4. Position of the vehicle in respect to the centre line of the lane to verify the presence of overload

The data sets collected during the trial about the variables speed, acceleration, radius, straight stretch, distance of visibility and CI function, treated through the process of subtractive clustering, allowed the sizing of the membership functions and rules as part of the fuzzy model.

In particular, the functions are Gaussians whose characteristics in relation to the mean, variance and the range of existence are given in Table 1.

The membership functions and Speed Straight Stretch were reported in Figs 6 and 7.

Table 1. Characteristics of the input membership functions

Name	MF	μ	σ	Interval
Speed (*S*)	$MF1_V$	72.00	10.75	[59.00; 91.00]
	$MF2_V$	79.00	10.75	
	$MF3_V$	74.00	10.75	
Acceleration (*A*)	$MF1_A$	0.00	1.30	[–2.09; 1.82]
	$MF2_A$	0.13	1.32	
Radius (*R*)	$MF1_R$	0.00	587.80	[–400.00; 1350.00]
	$MF2_R$	1350.00	587.80	
Straight Lenght (*SL*)	$MF1_{SL}$	21.00	72.55	[0.00; 216.00]
	$MF2_{SL}$	216.00	72.55	
	$MF3_{SL}$	0.00	72.55	
Distance of Visibility (*DV*)	$MF1_{DV}$	141.70	103.50	[62.48; 370.50]
	$MF2_{DV}$	128.90	103.50	
	$MF3_{DV}$	230.50	103.50	

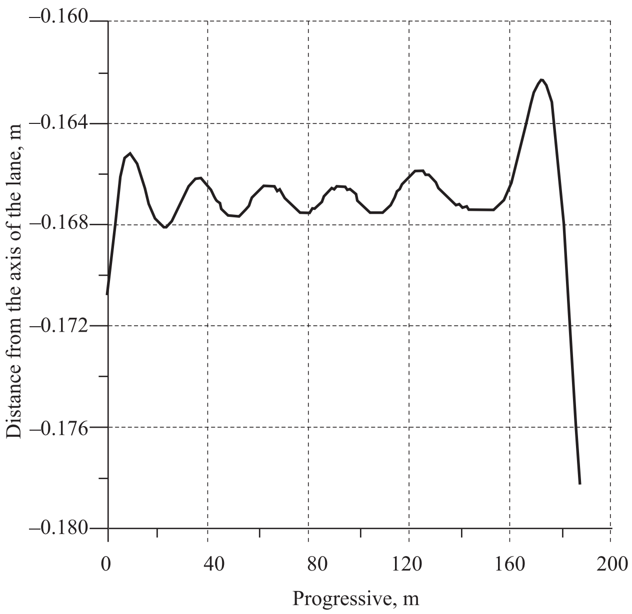

Fig. 5. Position of the vehicle in respect to the centre line of the lane to verify the presence of under load

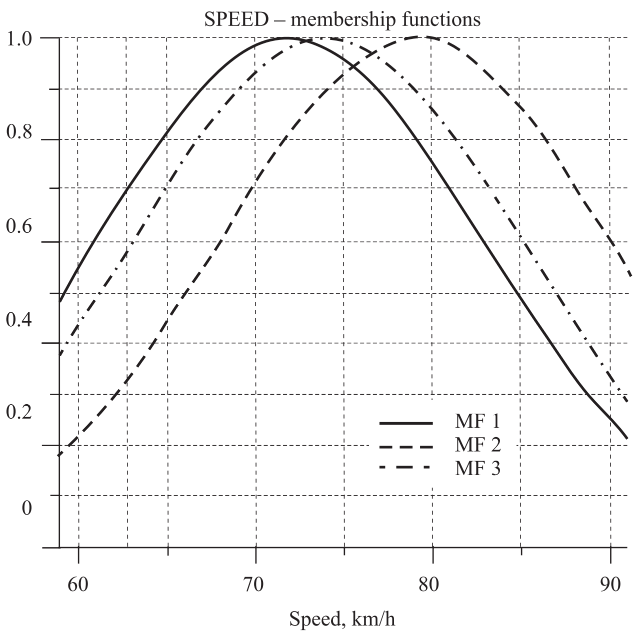

Fig. 6. Membership functions of the input variable speed

The definition of the input functions and the rules made it possible to obtain the value of the only crisp output function represented by the CI function.

Here below is a short part of the 18 rules introduced in the model.

1. If (S is $MF1_V$) and (A is $MF1_A$) and (R is $MF1_R$) and (SL is $MF1_{SL}$) and (DV is $MF1_{DV}$) then (CI is $MF1_{CI}$)
2. If (S is $MF2_V$) and (A is $MF2_A$) and (R is $MF2_R$) and (SL is $MF2_{SL}$) and (DV is $MF2_{DV}$) then (CI is $MF2_{CI}$)
3. If (S is $MF3_V$) and (A is $MF3_A$) and (R is $MF3_R$) and (SL is $MF3_{SL}$) and (DV is $MF3_{DV}$) then (CI is $MF3_{CI}$)
4. ….

In order to test the procedure the author has supposed a maintenance operation producing a decrease in speed of 10 km/h and an increase of 20 m of the distance of visibility.

The fuzzy model, under the new values, taken from some input variables, yielded a new CI function in accordance with the hypothesis which has been acquired of data sets (type of road user class, environmental, etc.). Fig. 8 shows the tendency of CI function depending on Trial (original configuration of the road) and Simulation (maintenance) in the most significant section (200–450 m).

Section 200–450 m – CI Function (Fig. 8): in the original configuration of the road CI function (continuous line) shows maxima at the bisecting curves, respectively, having a radius of 75 m and 70 m, agreed to the Land (1992) model where the driver looks preferably to the tangent point of the inner edge. Having interpreted the bend (ascending sinusoid to the point of max) the user turns his vision to the following geometric element (descending sinusoid). In the simulated configuration (dashed line), however, the 1st curve is interpreted with the same visual behaviour, except that the max value of the function is now slightly higher. The driver has rotated more his head-eye system. The 2nd bend, however, presents a succession of three sinusoids of different sign. In fact, the driver inside the bend does not look only at the inner edge but shifts his vision to the opposite side of the road and then returns to his original position.

Section 200–450 m – Cumulated Visual Energy (CVE) expended during the route: an examination of Fig. 9 shows increased visual activity in the simulated configuration, as if the introduced improvements have worsened the state of the driver. The paragraph on the discussion will be expanded on this result.

Section 200–450 m – Visual Energy expended versus time: VE(t) (Fig. 10) in the original configuration of the road (continuous line) there is presented a max at t = 10.5 s (beginning of bend R = 75 m), a min at t = 15 s (end of bend R = 75 m) and a max at t = 20 s (the middle curve R = 70 m).

The same Fig. 10, VE(t) in the simulated configuration presents a max at t = 12 s (initial part of the bend R = 75 m), a min at t = 14.5 s (end of curve R = 75 m) and two peaks at t = 18 and t = 22.5 s (the beginning and the mid-curve R = 70 m).

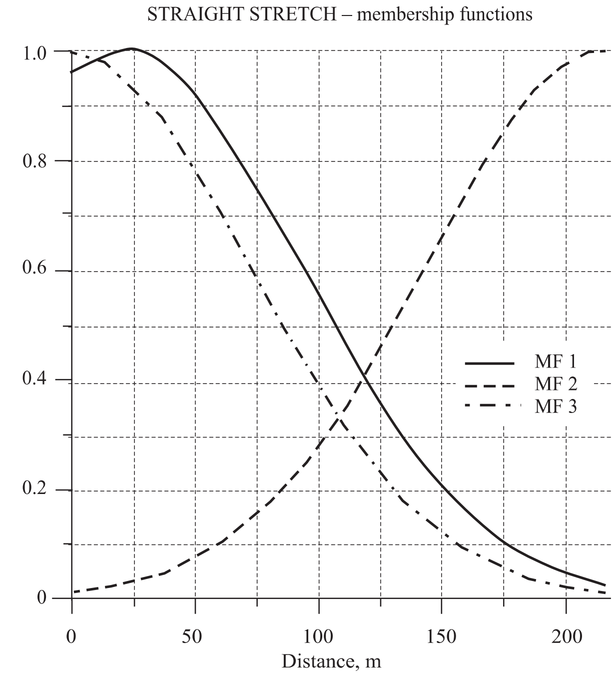

Fig. 7. Membership functions of the input variable Straight Stretch

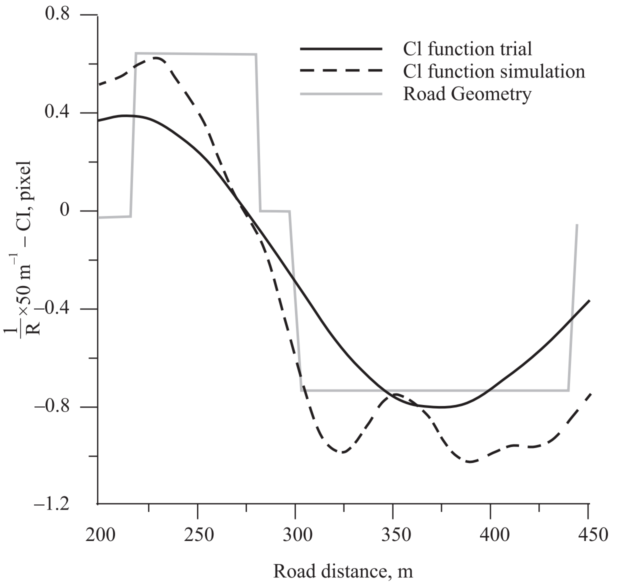

Fig. 8. Comparison of the CI function between the original and simulated scenarios in the section 200–450 m

Section 200–450 – Intensity of Visual Energy expended versus time: the IVE(t) (Fig. 11), in the original configuration of the road, there is presented a min at t = 13.5 s (about half curve R = 75 m) a max at t = 17 s (beginning of the bend R = 70 m) and a min at t = 22.5 s (end of the curve R = 70 m).

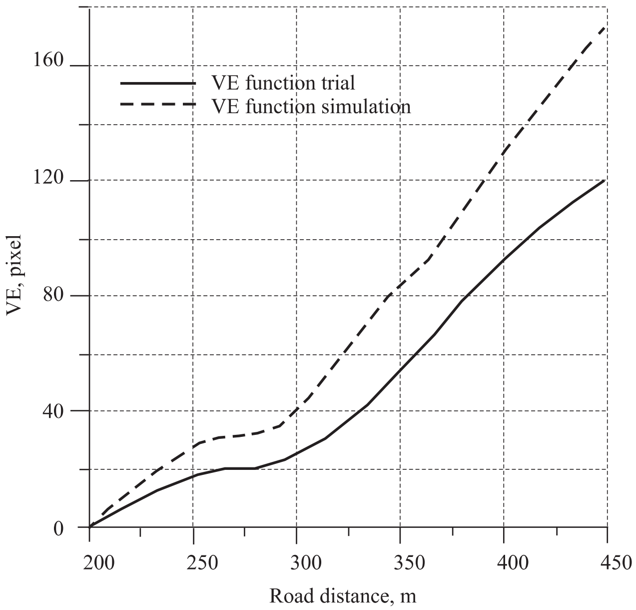

Fig. 9. Comparison of the CVE between the original and simulated scenarios in the section 200–450

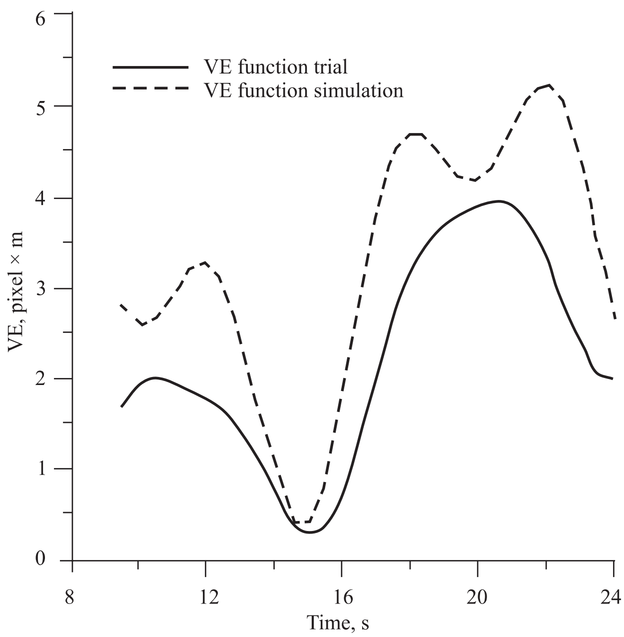

Fig. 10. Comparison of the Visual Energy between the original and simulated scenarios in the section 200–450 in relationship with the time

In the same Fig. 11, the IVE(t) presents, in the simulated configuration, a max at $t = 11$ s (beginning of the curve $R = 75$ m), a min at $t = 13.5$ s (about half curve $R = 75$ m), a max at $t = 16.5$ s (beginning of the curve $R = 70$ m), a min at $t = 19$ s (central part of the curve $R = 70$ m) and a further max at $t = 21.5$ s (central part of the curve $R = 70$ m).

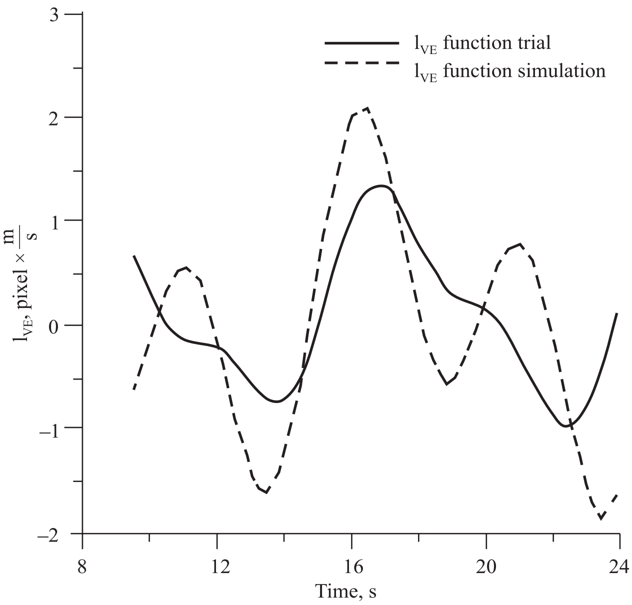

Fig. 11. Comparison of the Intensity of Visual Energy in relationship with the time between the original and simulated scenarios in the section 200–450 m

4. Discussion

In order to predict the workload on a section of an existing road after a maintenance intervention consisting of lowering speed by 10 km/h and an improvement in visibility distance of 20 m, a fuzzy model was introduced, based on a database built with head-eye movements data and the main dynamic characteristics of the vehicle.

The results seem very interesting, although some caution is needed in the formulation of conclusions.

At first, it is necessary to premise that the data sets acquired during the road trials served to determine the membership functions and rules that represent the points of greatest weakness of this technique. This procedure should thus provide good reliability of the final outcome.

The results, to a certain extent, are amazing. The author of this article thought the improved conditions of the route would lead to less frenetic and more relaxed visual activity. Instead, the user, having more time available, researches information also of normal visual field. This certainly gives a more visual work (see cumulative VE) but a better understanding of the environmental context, such as signs, particularly complex situations, marginal elements, etc.

The CI function in the original configuration of the road (continuous line) shows consistent behaviour with the findings of Land (1992; 2006). In particular, the user looks at the inner edge of the curve $R = 75$ m from the straight that precedes it (point of inflection of the CI function) and ends when he has already fully understood the geometry of the element (max point of the CI function).

The following bend (R = 70 m) also has a similar behaviour and the positioning of the min at the centre of the curve compared to the initial position is because the limited length of the straight that precedes it does not allow sufficiently early interpretation.

With the simulated configuration (dashed line) the driver has a different visual attitude. The max point of the first bend is located substantially in the same place. This means that the timing of the interpretation does not change. But the absolute value of the CI function is significantly greater a symptom that translates a more accurate visual scan.

The next bend in the simulated configuration has a peak at the beginning of the curve in a considerably more advanced position than the original configuration. This could be explained by the fact that driver had better conditions of visibility and, therefore, has understood the geometry of the next bend in advance. There is the presence of a small max, which indicates a direction of vision towards the outside of the visual field. This should not be intended as an unnatural visual mechanism but, rather, a possibility that the driver now has to evaluate other points of the environmental context.

Increased visual activity is evident in the figure that reports the cumulative VE in relationship with the distance travelled. This information can be used to provide an overall judgment of a sufficiently long road section. It does not provide, however, the opportunity to evaluate the individual geometric element as does the EV(t). This function sets the points of greatest visual load versus time and this information is crucial for the designer.

In this case, the original configuration of the road have only two peaks, located at the max of CI function, identifying the moment of greatest visual attention of the user. In the configuration simulated, however, there is another peak because of more frenetic visual activity. It should be noted that the first peak on the configuration simulated seems temporally out of phase than the original configuration because the speed is lower. But in space, the point beyond which the acquisition is finished is, however, anticipated.

It is also interesting to evaluate the user's effort, quantified by the derivative of VE versus time and that could be another parameter, together with the deceleration helping to identify a possible overload of the driver.

5. Conclusions

The complexity of the road system often highlights the inadequacy of routine road audits contained in the road standards and regulations. In recent years researchers have focused their attention on the weakest component: man. And among the more attractive proposals of variables to document the impact of the environment on drivers is certainly the workload.

An analysis of part of the vast existing literature permits the deduction of two things:

– there are many ways to calculate this variable according to the instruments used and the scope of human action;
– the predictive models currently available are very simplistic, often highly subjective, and however, they are based on not very developed analytical tools.

This paper is intended to contribute by proposing a model based on fuzzy techniques, built on a database recorded during several road tests with a properly instrumented vehicle.

The data set, regarding the visual activity of the driver and certain variables concerning the vehicle dynamic, has allowed the objective sizing of the membership functions and rules of fuzzy model.

These results are reassuring and encourage for further refining of the procedure. The positive consequences on the design stage is of great importance since that environmental context could be considered in more detail with respect to the traditional controls (lighting conditions, users belonging to particular categories, signs and road markings, etc.).

The model proposed here can only be used for maintenance on existing roads. This problem, in fact, still represents a limit surmountable only by extending considerably the size of data sets so most of the boundary conditions that may arise in the design of the new road may be included.

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