WHAT VARIABLES AFFECT TO A GREATER EXTENT THE DRIVER'S VISION WHILE DRIVING?

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Abstract. This paper deals with the analysis of the main variables involved in the visual activity of a driver of motor vehicles, in order to identify the most important quantities and implement, therefore, appropriate corrective actions to the achievement of road safety. The first step in this research was to survey a number of variables within the road environment and processing this data base with clustering techniques in order to extract useful information for purpose. In this case, a mixture of procedures based on Fuzzy Logic (FL) and Artificial Neural Network (ANN) were applied not only to extract knowledge not known a priori but, above all, to define the membership functions and rules of the fuzzy model without recourse to the skills of the analyst, not always so objective. This procedure, applied to a rural road open to traffic, showed a good performance in predicting the user's visual behavior and, especially, in identifying the most influential variables. This aspect may allow the agency to direct the maintenance operations so that to facilitate understanding of the information contained within the road environment, thus improving safety.

Keywords: visual behavior, driving behavior, road safety, fuzzy logic, ANFIS.

Introduction

The vision of people immersed in a complex environment, such as road, has been studied with profit by many researchers in the last thirty years. They immediately encountered some difficulties, such as the high statistical spread of the human factors involved, their relative numerousness, uncertainty and interdependence, which led the studies to represent in a qualitative way only a few observations concerning the phenomenon in question (Dorsey, Coovert 2003).

For example, among the most popular authors, Donges (1978) and Reid (1983) proposed a visual model behavior based on the combination of two mechanisms that take place in parallel. The first is a long-term process, according to the curvature predicted on the basis of the visibility of the stretch of road, while the second is a process in the short term operating in a corrective way allowing modification of the trajectory in the proximity to the roadside. Subsequently, although this mechanism was generally shared within the scientific community, a number of changes and clarifications were produced. For example, Godthelp (1986) has indicated that the two

stages operate in series rather than parallel and therefore the behavior performed during the forecast stage ends before the corrective stage is carried out. Latest researches (Land 1992; Grasso *et al.* 1998; Groeger 2000) have confirmed the correctness of these models, suggesting the importance of the tangent point as a reference for the approach to a bend and introducing certain time limits within which the driver triggers the feed forward and feedback mechanisms described above (Bosurgi, D'Andrea 2012).

Again Land (1998, 2006), Land, Horwood (1998) and Land, Tatler (2001) improved this theory, carrying out a number of experiments, also in simulated conditions and ascertaining that the edges of the road in the field of vision are the only necessary and sufficient visual cues for steering and understanding road geometry. These results are consistent with those based on optical flow and focus of expansion that were initiated by Gibson (1958).

With the development of modern eye-tracking systems, many researchers have studied more complex problems, related to the roto-translational components

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of the head-eye system movements and relating these to the road geometry (Rushton *et al.* 1998; Lappe *et al.* 1999; Wann, Land 2000, 2001; Wann, Wilkie 2003; Prévost *et al.* 2003; Erikson, Hörberg 1980; Miura 1990; Chapman, Underwood 1998a, b).

More recently Zariņš (2006); Antov *et al.* (2007); Konstantopoulos, Crundall (2008); Wood *et al.* (2009) and Bosurgi *et al.* (2010, 2011) emphasized the role of the visual scene in the strategies of drivers and, in particular, of the visual field on which to focus attention during critical events.

All these studies have the merit of having shown the basic mechanisms of visual behavior but did not produce any model able to predict the visual activity inside a complex environment. Tools to resolve these issues could reasonably be based only on soft computing techniques such as fuzzy logic, neural networks or genetic algorithms (Bosurgi, Trifirò 2005). Of course, the soft computing approach is not always preferable to other methods. It produces more realistic results when the number of variables involved is considerable and, especially, when their interdependence would render other techniques not applicable. If the nature of certain variables is also lexical, for example, the use of fuzzy logic should become necessary (Dubois, Prade 1998; Dağdeviren *et al.* 2008; Grassi *et al.* 2009; Pellegrino 2011, 2012; D'Andrea, Pellegrino 2012). For these reasons, the treatment of uncertainties in probabilistic terms is correct when the system consists of components whose reliability in a given period of time was measured and verified and whose variability is sufficiently small (Papoulis, Pillai 2002).

1. Aim of the Paper

In recent years, the development of modern digital instruments has enabled the survey of large amounts of data that, however, must be properly sorted and understood in order to extract useful information. Moreover, the preventive treatment of the data set is of paramount importance when using artificial intelligence techniques because it allows to prepare the preliminary stages of training, absolutely necessary to achieve credible results.

Generally, fuzzy logic, by means of fuzzy if-then rules, can model some qualitative aspects of human knowledge applying linguistic or analytical information. Unfortunately, it possesses disadvantages regarding rules and membership functions that have to be tuned by subjective judgment in order to achieve the desired reliability. To overcome these limitations, recent researches have proposed the support of artificial neural networks and the result, an adaptive network-based fuzzy inference system, has been shown to be an efficient tool because of a hybrid learning procedure for calibrating the membership functions and the rules (Jang 1993; Güler, Übeyli 2005; Mon 2007; Gu, Oyadiji 2008; Tahmasebi, Hezarkhani 2010).

With this paper, the authors wanted to propose a method that, starting from the visual drivers' behavior, would allow identification of the critical aspects in the road environment, in order to eliminate them at an early stage of design. In the first phase, the observed data set was analyzed with neuro-fuzzy techniques for a dual purpose: to identify the most important variables in relation to the visual behavior and to remove subjectivity in the preparation of the membership functions and rules. The predictive model returned, as an output variable, a function representative of visual behavior, that is the head-eye movement (EM) but, more importantly, it allowed prediction of this with varying of the input parameters, depending on a road, user and vehicle. This consents, in the case of critical visual behavior, modification of one or more characteristics of the road (as radius or distance of visibility) in order to have an optimal driver's visual response towards road safety.

2. Method

The procedure followed in this research begins with preliminary trials on a rural road regularly open to traffic by a suitably instrumented vehicle capable, that is, to record the user's head-eye movements by means of Image Analysis (Gonzales, Woods 2002; Jha 2006), its activity on the pedals, some dynamic parameters of the vehicle and the geometric characteristics of the road (Bosurgi *et al.* 2004, 2007; Pellegrino 2009). It was subsequently prepared a predictive model that links some input variables related to the road environment and to driver's visual activity that, therefore, represents the output. The collected data base was used, as mentioned, both during calibration of the fuzzy model to train and check the procedure.

The preparation of a predictive model used in maintenance operations, requires the development of a number of preparatory steps and, especially, the identification of variables involved in the phenomenon and the characterization of their uncertainty. The choice to represent the variables with the neuro-fuzzy system allows the use of natural language through the judgments of the experts, the achievement of flexibility in the model, tolerance to inexact data, and the possibility of representing non linear functions of arbitrary complexity.

2.1. Brief Notes about Fuzzy Logic (FL) and ANFIS

In the traditional theory, a Membership Function (MF) or $\mu_A(x)$ is a function that defines how each point of X in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Fuzzy operators represent the verbs of fuzzy logic and the 'if-then-else' rule statements are used to determine all the conditional definitions. The if-part of the rule is called the antecedent, while the then-else part of the rule is called the consequent. It will be necessary firstly to fuzzily the input (that is to calculate the antecedent) and then, by means of the implication process, to apply this result to the consequent. The consequent specifies a fuzzy set assigned to the output. The implication function then modifies that fuzzy set to the degree specified by the operator in the premise. The most common means of

modifying the output fuzzy set are truncation using the main function or scaling using the product function (Chao 2007).

Generally, fuzzy models can present certain problems regarding the definition of membership functions and rules that bind the dependencies between the variables involved due to the excessive subjective contribution of the analyst. This problem can overcome through the use of clustering procedures, applying them to the relevant data that will then be interpreted, organized and classified in an appropriate manner (Lin, Lee 1996; Li *et al.* 1999; Sarimveis *et al.* 2003).

In fact, these methods are used to identify experimental groupings of data from a large data set to produce a synthetic representation of a system's behaviour through optimal membership functions. For example, neuro-fuzzy techniques exploit Artificial Neural Networks (ANNs) procedures to determine the properties of fuzzy sets and fuzzy rules by processing data sets. The most famous approach in this field is the Adaptive Neuro-Fuzzy Inference System (ANFIS), in which the membership function parameters and the rules are extracted from a data set opportunely surveyed (Jang 1993). The model is trained with the back-propagation gradient descent method and because of slowness, is preferable combined with the least squares method. In brief, the steps can be outlined thus:

- collect a training data set that contains the desired input/output data of the system to be modelled;
- specify an initial model structure (in this case, it was the Sugeno type);
- after generating the initial fuzzy model structure, it is possible to train it by means of the back-propagation form of the steepest descent method; the optimization method train the membership function parameters to emulate the training data;
- it is opportune to specify the number of training epochs and the training error tolerance to set the stopping criteria for training;
- after the fuzzy model is trained, the model can be validated using a testing or checking data different from that used.

The steepest descent method is a first-order optimization algorithm. To find a local minimum of a function this procedure takes steps proportional to the negative of the function gradient at the current point. If instead the steps are proportional to the positive of the gradient, a local maximum of that function has been approached.

To illustrate the methodology behind this procedure, we can introduce a simple example with two fuzzy if-then rules based on a first order Sugeno model (Fig. 1):

$$\text{Rule 1: if } \left(x \text{ is } A_1 \right) \text{and} \left(y \text{ is } B_1 \right)$$

$$\text{then} \left(f_1 = p_1 \cdot x + q_1 \cdot y + r_1 \right); \tag{1}$$

$$\text{Rule 2: if } \left(x \text{ is } A_2 \right) \text{and} \left(y \text{ is } B_2 \right)$$

$$\text{then} \left(f_2 = p_2 \cdot x + q_2 \cdot y + r_2 \right), \tag{2}$$

where: x and y are the inputs; A_i and B_i are the fuzzy sets; f_i are the outputs; p_i, q_i and r_i are the design parameters that are determined during the training progression. In the Fig. 1 a circle indicates a fixed node and a square is an adaptive node. The first layer is composed by adaptive nodes and the outputs are the fuzzy membership grade of the inputs, given by:

$$O_i^1 = \mu_{A_i} \left(x \right) \text{ with } i = 1, 2; \tag{3}$$

$$O_i^1 = \mu_{B_i - 2} \left(y \right) \text{ with } i = 3, 4, \tag{4}$$

where: $\mu_i \left(x \right)$ could be described by the generalized Bell function:

$$\mu_i \left(x \right) = \left(1 + \left(\frac{X - c_i}{a_i} \right)^{2 \cdot b_i} \right)^{-1}, \tag{5}$$

where: X is the input; a_i, b_i and c_i are adaptable parameters.

In the second layer, there are only fixed nodes and they are simple multipliers (*M*). The outputs can be expressed as:

$$O_i^2 = w_i = \mu_{Ai} \left(x \right) \cdot \mu_{Bi} \left(y \right) \text{ with } i = 1, 2 \tag{6}$$

called the firing strengths of the rules.

Also in the third layer, the nodes, labelled with *N*, are all fixed. They normalize the firing strengths from the previous layer. The outputs can be reported as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \text{ with } i = 1, 2. \tag{7}$$

In the fourth layer, there are only adaptive nodes. The output is the product of the normalized firing strength and a first order polynomial:

$$O_i^4 = \overline{w}_i \cdot f_i = \overline{w}_i \cdot \left(p_i \cdot x + q_i \cdot y + r_i \right) \text{ with } i = 1, 2. \tag{8}$$

In the fifth layer, there is a single fixed node (*S*) that sums all incoming signals:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i \cdot f_i = \frac{\sum_{i=1}^{2} w_i \cdot f_i}{w_1 + w_2}. \tag{9}$$

It can be observed in the first adaptive layer, there are three modifiable parameters (called premise parameters) a_i, b_i, c_i, related to the input membership functions.
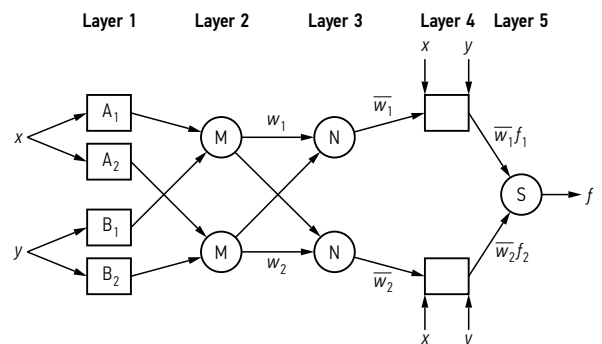

Fig. 1. ANFIS architecture

In the fourth adaptive layer, there are different modifiable parameters (called consequent parameters) p_{is}, q_i, r_i, pertaining to the first order polynomial.

The learning algorithm is designed to calibrate all the modifiable parameters as $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the output compatible with the training data.

When the membership function is fixed, the output can be written as:

$$f = \frac{w_1}{w_1 + w_2} \cdot f_1 + \frac{w_2}{w_1 + w_2} \cdot f_2 \qquad (10)$$

and, finally:

$$f = \overline{w}_1 \cdot f_1 + \overline{w}_2 \cdot f_2. \qquad (11)$$

Substituting the fuzzy if-then rules into the last equation:

$$f = \overline{w}_1 \cdot \left(p_1 \cdot x + q_1 \cdot y + r_1\right) + \overline{w}_2 \cdot \left(p_2 \cdot x + q_2 \cdot y + r_2\right). \qquad (12)$$

In this way and after some rearrangement, the output can be expressed as:

$$f = \left(\overline{w}_1 \cdot x\right) \cdot p_1 + \left(\overline{w}_1 \cdot y\right) \cdot q_1 + \left(\overline{w}_1\right) \cdot r_1 + \left(\overline{w}_2 \cdot x\right) \cdot p_2 + \left(\overline{w}_2 \cdot y\right) \cdot q_2 + \left(\overline{w}_2\right) \cdot r_2. \qquad (13)$$

As mentioned, a hybrid algorithm combining the least squares method and the gradient descent method can be used to identify in a faster way the optimal values of these parameters, especially when the premise parameters are not fixed.

In particular, when the premise parameters are fixed, the least squares method (forward pass) is used to optimize the consequent parameters. Once the optimal consequent parameters are found, the gradient descent method (backward pass) is used to adjust in an optimal mode the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by using the consequent parameters already found in the forward pass, while the output error permits to adapt the premise parameters with the back-propagation algorithm (Jang 1993).

In order to acquire a complete data set covering the aim of the present research, a survey on a rural road near the town of Messina (Italy) was organized with an instrumented vehicle and a homogeneous sample of users. A number of features are outlined below, and further details are specified in references (Bosurgi *et al.* 2004, 2007; Pellegrino 2009).

2.2. The Trial Vehicle

Equipment for tracking eye movement, the road environment and dynamic vehicle were installed on a Ford Focus (Fig. 2).

The instruments included three micro cameras, concealed within the car interior to avoid obtrusiveness. The first of these provides a reasonably faithful picture of the driver's view ahead, the second reproduces the view through the rear-view mirror and the third records head and eye movements in greater detail.
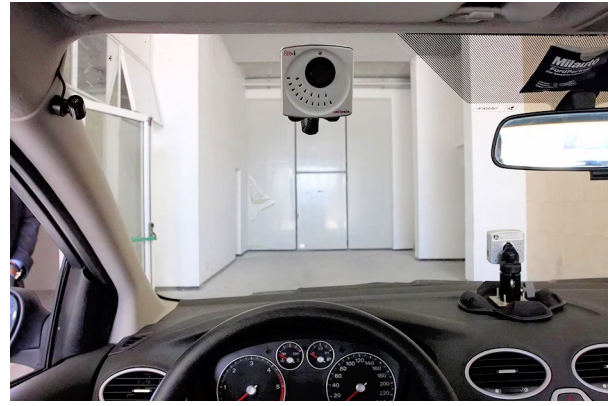

Fig. 2. Two of three cameras inside the cockpit

Special software was written to coordinate this instrumentation since our highly specific requirements made it impossible to use any of the more standard commercial applications (Bosurgi *et al.* 2004, 2007). This application also allowed the calculation of head-eye system coordinates in real time and using Image Processing techniques (Gonzales, Woods 2002).

2.3. Road Analysed

Before beginning the road trials, the Authors selected 12 male drivers between the ages of 25 and 28 who, therefore, had between 7 and 10 years of driving experience and who were all habitual users of the sections of road under examination. The trials took place on a country road over a distance of about 7.5 km with a uniform track in terms of cross section and construction.

Morphological-geometrical features are as follows:
 – the cross section comprises two separate carriageways constructed at equal height, with three lanes each of which is 3 m in width;
 – there are two footpaths of 1.40 m each positioned alongside the edge of the carriageways; the one on the coastal side is fitted with a safety barrier;
 – the central reservation is planted over and varies in width from 2.5 m to 4.00 m;
 – the trials were carried out on the carriageway nearest to the hills, using a sample group of eight drivers;
 – the radii vary between 70 and 160 m.

The trial lasted for about 10 minutes and took place under the normal traffic conditions with participants unaware either of the aims of the study or of the presence of instrumentation within the vehicle. The vehicle was also occupied by an operator responsible for making sure the computer and tracking equipment worked properly.

2.4. Variables Involved

The main parameters involved in this experiment, as already mentioned, are all related to the drivers' behavior, to vehicle dynamics and road context. These variables may be listed as follows:
 1) movements of head-eyes system (*EM*): *X* and *Y* coordinates of the pupil centroid in a Cartesian

system in which the unit of measurement is the pixel;
2) distance between pupil centroids in pixels;
3) angle of line joining centroids relative to horizon line in centesimal degrees;
4) vehicle speed (*Sp*) in km/h;
5) vehicle longitudinal acceleration (*Ac*) in m/s^2;
6) circular curve radius (*R*) in m;
7) distance of visibility (*V*) in m;
8) straight stretch (*St*) in m;
9) accelerator pedal percentage use in %;
10) longitudinal grade of the road (*Al*) in %.

The trend of head-eye movements (*EM*) with respect to the geometry allows the evaluation of the visual strategy of the driver while checking the homogeneity with the standard literature. In particular, idealizing the trend of EM function with a sinusoid, at the inflexion point, a driver began to interpret the bend, looking at the tangent point of the curve. In the max (or min) point, this interpretation was completed. Therefore, in the distance covered from the inflexion point and the max (or min) point, the driver interprets the road geometry.

During the trial, some of these variables (such as distance between pupil centroids, angle of line joining centroids activities on the pedals) have proved uselessness in this initial phase of research for the interpretation of visual behavior. At the end, six input variables were selected, trained and then checked. However, these six variables, as is easily guessed, are not all of equal importance in determining the output. Therefore, the purpose of the procedure was to identify which are the most influential both individually and in groups. The index used by the authors to appreciate the fairness of the procedure was the Root Mean Square Error (RMSE), although there are other statistical parameters that there will not discuss for reasons of brevity. The RMSE is a measure of precision by means of the differences (called residuals) between values predicted by a model and the values actually observed from the thing being estimated. In this paper, the normalized root mean square error has been used, obtained as RMSE divided by the range of observed values. The result is, therefore, expressed as a percentage, where lower values indicate less residual variance.

3. Results

As a first step, we evaluated the input variables that most influence the head-eye movements that are the output of the model. ANFIS techniques (Chiu 1996) outlined above have allowed to perform some experiments whose results were reported in Tables 1–3.

A part of the surveyed data set (1200 observations of 1456) was used to train and build the model. The remaining observations (256) have been used to test the capability of the model to be applied to general cases. However, after the first configuration, the model must be calibrated, i.e. it must be optimized based on training errors or, rather, checking. In fact, it may be that the model over-fits the training data, i.e. it responds well

Table 1. Training and checking errors with an input at a time

		Training	Checking	T–C
1	Sp	0.2605	0.3427	0.0822
2	Ac	0.2232	0.3793	0.1561
3	Al	0.2457	2.2415	1.9958
4	R	0.2241	2.1665	1.9424
5	St	0.2693	0.3474	0.0781
6	V	0.2778	0.3899	0.1121
			min	0.0781

Table 2. Training and checking errors with two inputs at a time

		Training	Checking	T–C
1	Sp–Ac	0.1663	0.4542	0.2879
2	Ap–Al	0.1943	1.9251	1.7308
3	Sp-R	0.1444	4.5428	4.3984
4	Sp–St	0.2350	0.3827	0.1477
5	Sp–V	0.2354	0.9490	0.7136
6	Ac–Al	0.1662	2.4592	2.2930
7	Ac–R	0.1519	10.0494	9.8975
8	Ac–St	0,1847	0.4717	0.2870
9	Ac–V	0.2040	0.4710	0.2670
10	Al–R	0.1347	54.2134	54.0787
11	Al–St	0.2317	2.7157	2.4840
12	Al–V	0.1972	2.5358	2.3386
13	R–St	0.2002	0.4562	0.2560
14	R–V	0.1591	2.7407	2.5816
15	St–V	0.2309	1.1431	0.9122
			min	0.1477

Table 3. Training and checking errors with three inputs at a time

		Training	Checking	T–C
1	Sp–Ac–Al	0.1149	1.9345	1.8196
2	Sp–Ac–R	0.0939	34.3076	34.2137
3	Sp–Ac–St	0.1094	0.5353	0.4259
4	Sp–Ac–V	0.1107	0.8679	0.7572
5	Sp–Al–R	0.0925	157.7875	157.6950
6	Sp–Al–St	0.1759	1.0810	0.9051
7	Sp–Al–V	0.1543	6.5021	6.3478
8	Sp–R–St	0.1071	8.3299	8.2228
9	Sp–R–V	0.1014	72.7484	72.6470
10	Sp–St–V	0.1917	3.2527	3.0610
11	Ac–Al–R	0.0837	72.5316	72.4479
12	Ac–Al–St	0.1438	1.4571	1.3133
13	Ac–Al–V	0.1325	2.0242	1,8917
14	Ac–R–St	0.1055	2.1979	2.0924
15	Ac–R–V	0.1210	10.0659	9.9449
16	Ac–St–V	0,1259	1.1218	0.9959
17	Al–R–St	0.1052	238.7862	238.6810
18	Al–R–V	0.0828	345.2563	345.1735
19	Al–St–V	0.1602	2.6468	2.4866
20	R–St–V	0.1061	22.4941	22.3880
			min	0.4259

only in the scenario used for surveying but not to represent more general situations. In this case, it is necessary to minimize RMSE in function of the number of epochs that, therefore, is a means to tune the model.

For optimal selection of input variables inside the ANFIS model, an exhaustive search has been conducted organizing an ANFIS model with a certain number of input variables (respectively 1, 2 and 3) and trains it for the number of input combinations and one epoch and reporting the results achieved in term of Mean Quadratic Error (MQE) for training and checking data.

This procedure was based on the hypothesis that, the model with the smallest residual MQE, after the first training iteration, has a better estimation than the other configuration to reach a smaller MQE even with a higher number of iterations. The first step to run the process was to specify to be tried during the search.

For example, with reference to the Table 1, the variables Speed *(Sp)* and Straight Stretch *(St)* have the least error or, in other words, the most relevance with respect to the output. The training and checking errors are comparable, which implies that there is no overfitting. In view of these results, it was subsequently evaluated the influence of two variables, selecting more than one input attribute to build the ANFIS model.

ANFIS was built with the same procedure respectively, it means with the combination of two and three inputs for a time (Tables 2 and 3). The results clearly indicate a strong influence of the variables *Sp* and *St* (already emerged with the first assessment) even with the addition of the longitudinal Acceleration *(Ac)*.

The results from the previous simulations show that Speed *(Sp)* and Straight Stretch *(St)* are the best combination for the ANSIS model but now, with the next step, it is necessary to spend more time on training. In order to know with some approximation the number of epochs that provides a better approximation, we calculated the errors of the training and checking data. From Fig. 3, it can be easily highlighted the error training function that has a minimum around 850 epochs, therefore, represents the optimal number for simulation of the model.

In Fig. 3, the curve of the training error is determined by the difference between the surveyed output and forming part of the training data set and the output of the model built with the input data of the training data set. In particular, this difference is reported in terms of RMSE as a function of the number of epochs; the minimum value of RMSE identifies the optimal value of epochs to train the model.

Similarly, also the checking error curve is quantified as a function of the number of epochs and representative of the difference between the surveyed output and forming part of the checking data set and the output of the model built with the checking data set. The value of RMSE translates the capacity of the model to simulate the phenomenon that we want to represent. The minimum value on the curve of checking is particularly important because, for a large number of epochs and data it is possible that the training function shows problems of overfitting in the model and, therefore, it can not be used to calibrate the model.
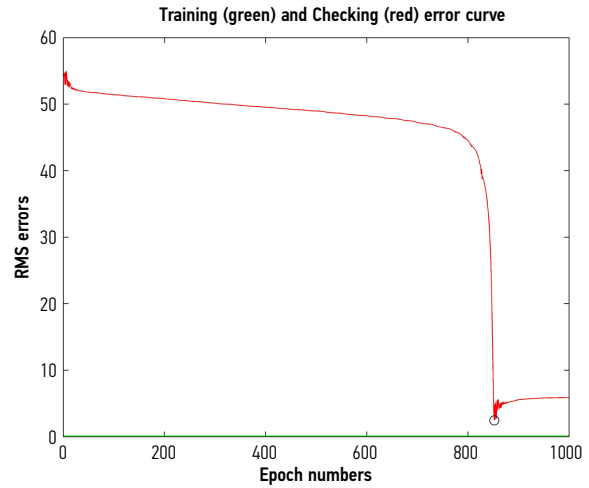

Fig. 3. Determination of the best number of epochs by means of training (green) and checking (red) curves

The data sets collected during the trial and tuned with the ANFIS procedure, allowed us to size the membership functions and rules that are a part of the fuzzy model. In particular, the functions are Gaussians whose characteristics in relation to the mean, the variance and the range of existence are given in Table 4.

Table 4. Characteristics of the input membership functions

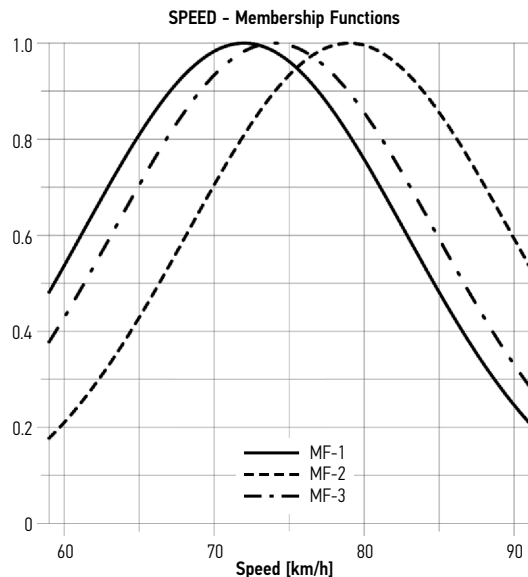| Name	MF	μ	ρ	Interval
	$MF1_{Sp}$	72.00	10.75	
Speed *(Sp)*	$MF2_{Sp}$	79.00	10.75	[59.00; 91.00]
	$MF3_{Sp}$	74.00	10.75	
	$MF1_{St}$	21.00	72.55	
Straight Stretch *(St)*	$MF2_{St}$	216.00	72.55	[0.00; 216.00]
	$MF3_{St}$	0.00	72.55	

Fig. 4. Membership Functions (MF) of the input variable Speed *(Sp)*

The Figs 4 and 5 represent the tendency of the input membership functions Speed and Straight Stretch respectively.

The preparation of membership functions and rules, allowed the value of the one crisp output function to be derived, represented by the Eye Movement (EM) function.

A simulation with the neuro-fuzzy model has finally allowed to build a new EM function in accordance with the hypothesis which was acquired of data sets (type of users class, environmental context, etc.). Fig. 6 show the tendency of EM function in a section of road (650÷1000 m) considered more significant, with two curves in the opposite side with a radius of 160 m.
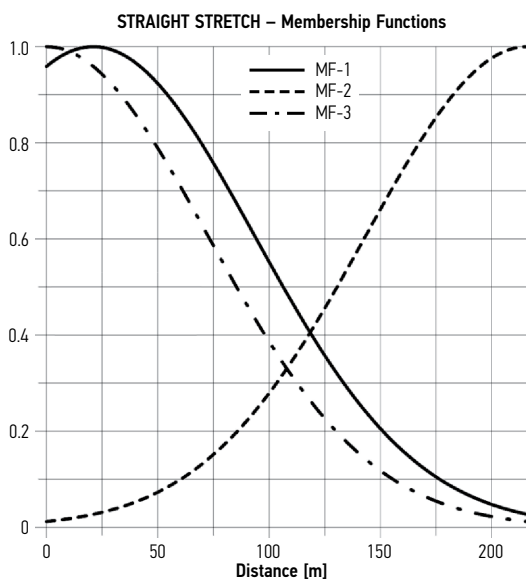
Fig. 5. Membership Functions (MF) of the input variable Straight Stretch (*St*)
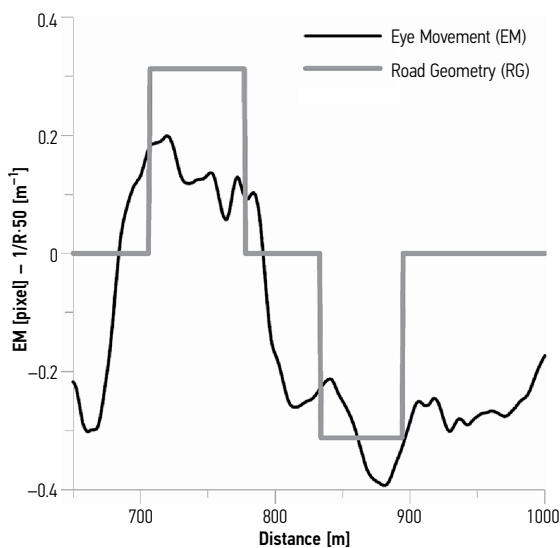

Fig. 6. Comparison of the Eye Movement (EM) function with the Road Geometry (RG) in the section 650÷1000 m

4. Discussion

This study aims to evaluate the visual behavior of road users and the difficulties linked to this.

The first one concerns the extraction of useful information from modern digital devices that survey the quantities of interest at frequencies so high to assume an unmanageable size. Recently, with the increase of technological progress, it is possible to record at low-cost several parameters relating to dynamic of the vehicle, driver's eye movements, characteristics of the road geometry and of the entire context. The problem arises when you want to evaluate the uncertainties and the dependencies between these variables and the laws governing the phenomena of interest. If you want to leave the confines of the observation of the phenomenon, already dealt with successful in much in-depth research into existing literature and want to propose a model that will aid in making predictions, the variables involved should be managed in a more appropriate way. These are not all equally important, show interdependency between them and the functions describing the observed phenomenon are sometimes nonlinear and non differentiable. Therefore, they not only become almost mandatory to use the artificial intelligence techniques, but also must be preceded by the opportune clustering procedures in order to make a disorganized data base in a source of useful information to the purpose. The process of clustering, however, configures in the best way the basic elements of the model (in this case the membership functions and rules of the fuzzy model), eliminating any subjective influence of the analyst.

In particular, the ANFIS technique has directed us towards a model with only two inputs and one output. However, there were also analyzed and performed simulations, respectively, with one and three input variables at a time. Authors like the model with two input variables, in which the pair *Sp–St* has a value of checking RMSE particularly low (0.3827). Values of the same order of magnitude can be found in the table 1 (with only one variable) but the model so formed is not very useful because it is too simplistic.

The examination of the tables for these attempts shows that the results are, however, all consistent with each other. For example, in the case of one variable (Table 1) the Straight Stretch (*St* = 0.0781) presents a smaller difference between the errors of training and checking but the Speed (*Sp* = 0.0822) has a value very similar to the first. It should be noted that the Radius (*R*) and Acceleration (*Ac*) have low values of error for the training phase, which, however, grow considerably during the checking one. This implies that the variables that have a greater influence in determining the visual behavior are certainly *St* and *Sv*, followed by *R* and *Ac*. These considerations are fully compatible with the observations reported by most researches that attributed with a great importance especially to the straight before the bend as the driver begins to interpret the next element in advance depending by radius and speed of the vehicle.

The simulation with two inputs at a time, different combined (Table 2), confirms the information revealed previously. The couple *Sp–St* (0.1477) is the most powerful, but good results are also provided by the pairs involving *R* and *Ac*. Other variables, such as the longitudinal slope of the road (*Al*) present the major differences between the training and checking errors, proving to be unreliable.

The simulation with three inputs at a time, different combined (Table 3), produces the same information. The best choice falls on *Sp–Ac–St* = 0.4259. This value is still acceptable, but the increased difference between the phase of training and checking may indicate a principle of overfitting of the data. So, for prudence, it was decided to calibrate the prediction model with only two inputs, i.e. the Speed (*Sp*) and the Straight Stretch (*St*).

Knowledge of training and checking errors made it possible to determine the temporal period in which to train the model. Fig. 3 shows well that the test should be extended to approximately 850 epochs. At the end of this procedure of calibration, the membership functions and rules (Table 4, Figs 4 and 5) have been defined in an objective way.

The proposed procedure allows, however, to update the architecture of the model with easiness in case of new available survey data. And, however, it is possible to estimate the reliability of the model through the control of errors and the number of epochs required for training phase.

An application of this model has simulated the driver's visual behavior on a section of an existing road. In order to evaluate any congruence with the results of the literature, head-eye movements (EM) were superimposed on the road geometry (RG). From Fig. 6 it follows a trend of EM at first very irregular. However, with greater attention, it is possible to recognize a good consistence between the EM and the RG functions, especially in correspondence of the two bends. In fact, there is a substantially sinusoidal pattern of EM, which is compatible with the mechanism of feed-forward and feedback introduced by Donges (1978) and subsequently developed by Land (1992, 1998). The user has started to turn the system head-eye a few seconds before entering the bend, gazing at the tangent point at a distance dependent on the speed. Within the two curves, but especially in the first, it is possible to notice irregular trends of EM, induced by the driver's control on the different points of the visual field (feedback mechanism). This action, carried out by looking at the rearview mirrors or other points in the windscreen, it is useful to the safety of the vehicle because it can produce repositioning within the lane if it were needed.

With reference to the models existing in the literature, an ideal pattern of eye movements in relation to road geometry would be illustrated by a sine wave. The inflection point should pass at the straight before the analyzed bend and it should identify the beginning of the interpretation of the curve. The maximum (or minimum) point would represent the deviation of the driver's eye-head system toward the internal edge and,

therefore, the final point beyond which driver believes to have interpreted the geometric element and turns his gaze to the subsequent elements of the road. This ideal performance rarely takes place in reality, unless an entire sample of users is considered. Although the general trend of EM function could be simplified through a sine wave, it is also interesting to find the presence of additional peaks of the small amplitude and wavelength that means small eye movements. The gaze is deviated for a very short time from the target to capture all the possible information inside the visual field. Examination of the movies made it clear that this behavior occurred with two distinct situations: first, the driver had sufficient time (low speed and good sight distance) to inspect in detail the visual scene in its extension; the second case occurred when the context was so complex to suggest different areas of the visual field on which to place attention. Therefore, since the aim of this research is to guide the maintenance in order to improve the visual interpretation of the driver, is not important to use an eye tracking instrument of great precision.

This application at a short section of this road explains the use that can have the model here proposed. Since the visual behavior is related to the proper interpretation of the road and, therefore, to the road safety, we could test some maintenance operations (as the modification of the radius of a bend or the visibility distance or imposing speed limits) and verifying the effectiveness not only with the road standard, but above all, with the natural mechanism followed by the users to acquire visual information by means of road context.

Conclusions

The contribution of this research is not limited to a simple application of soft computing techniques to the current vision models but deals with some problems still undetermined:

- The existing models connect the visual behavior only to the road geometry (radius, curve and straight length, angle of deviation between the straights).
- The existing models do not permit an analysis of prediction. This is due to the reduced number of variables and analytical models too simplistic compared to the complexity of the road environment.

In general, the dependences between variables are difficult to interpret, often non-linear and would lead to an inability to obtain useful solutions. Therefore, the analyst generally chooses between two different possibilities: models extremely simple, but unrealistic, in which the variables can be treated by deterministic or probabilistic techniques. Or, models that take into account the real uncertainties and, above all, the bonds that are created between the quantities involved in the observed phenomenon. A model such a complex can only be treated with artificial intelligence techniques, as in the case of this paper. The proposed model, furthermore, has the advantage that can be updated with ad-

ditional variables without losing accuracy (but, rather, increasing it) in the calculation of final solutions.

In this paper, the results have confirmed those of the literature. This was not the final point of the present study, otherwise there would be no any change and the use of artificial intelligence techniques would have been unjustified. But it was, on the contrary, a necessary starting point, a sort of benchmark, without which the proposed model would not have had the proper recognition for subsequent analysis.

Again, no particular emphasis was given to the system for measuring eye movements in terms of accuracy, tolerance, etc., but instead we used a simple system of medium-quality cameras and on the recorded video we have applied some image analysis techniques that have established the visual zones in which the user's gaze focused. Do not forget, in fact, that the purpose of this research is not to investigate diseases or eye movements frequency of particular entities or to propose automotive instruments of particular innovation (and cost), but rather build a system capable to relate driving visual activity with road context so the latter can be corrected or mitigated to improve the perception.

Another new element emerged from this study is that the variables do not really have all the same weight. This assumption can be verified only through an analytical technique such as that proposed by the authors. A deterministic or probabilistic model would be extremely complex to organize and solve, if not assuming boundary conditions particularly simple and therefore not very realistic. Finally, the introduction of new variables or new data would have needed a totally new model with improved costs.

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