Lane Marker Parameters for Vehicle's Steering Signal Prediction

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Abstract: - The work considers road lane parameters that correlate with steering angle of a car and which are suitable for accurate prediction of steering signal using neural network technique. Four different parameters, which can be used in driver's assistance system and are based on position, angles and curvature of the lane marker, are proposed and their correspondence to steering signal is analyzed. The steering signal is predicted with the precision of 95% to 97%, depending on a combination of the visually-based parameters provided for the neural network. The work is performed using signals from real road driving.

Key-Words: - Steering signal, lane marker, vehicle, correlation, human-like driving, neural network

1 Introduction

A lane marker on a road can provide useful information for vehicle's control. However, a direct use of the lane marker shape for the vehicle's control is complicated; therefore it should be parameterized by features which are correlative to driver's behavior during a drive. The drivers' behavior is complex and it involves braking, acceleration / deceleration, steering, so design of reliable driver's assistant system for the full driver's behavior prediction and assistance at different driving conditions is a challenge. The assistance in a single drivers's action, e.g. steering or braking, is possible and such systems are already integrated in modern vehicles.

It is important to notice a difference between intelligent and conventional driver's assistance systems (DAS). The conventional DAS do not take into account individual driver's behavior, i.e. the control provided by the system is clearly based on physical laws and automata theory [1]. For example, such systems were developed and demonstrated under the integrated European project PReVENT [2]. In this case the DAS do not take into account human-like driving [3-5]. The intelligent DAS are adaptive to individual driver's behavior, therefore a vehicle becomes personalized to a single driver. Moreover, the adaptation process of the intelligent DAS can be performed during full lifetime of the system.

The objective of the work was estimation and analysis of four different lane marker parameters highly correlative to a vehicle's steering signal and prediction of a steering signal using the estimated parameters. The presented parameters are estimated from data recorded during usual driving on country roads and the results are compared with steering signal evaluating cross-correlation coefficients between them. The steering signal was predicted using neural network technique using different combinations of the estimated parameters for the network training and testing.

2 Data

Volkswagen Passat was used as a test car for recording of driving data. The driving action sequences simultaneously with traffic scenario were recorded and stored in a personal computer. The driving data was collected on country roads in Germany. The records were done in 2006, 2007 and 2008 years by different drivers at different routes.

The driving data, analyzed in the work, can be separated in two different parts. The first part of the data consists of information provided by a CAN-bus. It takes into account driver's behavior (steering, braking, acceleration, etc.) and includes information related to the vehicle (velocity, vehicles position on a lane, etc.). The other part of the data, the visual one, was captured by a video camera installed in the car. Dimensions of the images were 1280×1024 pixels. The right side lane marker data (x and y coordinates in pixels) were extracted from these images using an algorithm, presented in our previous work [6]. During the analysis more than 28000 images were processed in total.

3 Parameters

In our previous work [7] it was estimated that steering signal prediction error cannot be reduced by joining together (e.g. with a neural network) several sensor input signals of very low correlation to the steering signal, e.g. acceleration and velocity. Therefore the features which are highly correlated to the steering signal should be used in the neural network training. It should be noted that the lane marker parameters are extracted from a visual data which is noisy. However, the neural network can be trained by a single feature, but more different features of relatively high correlation to the steering signal reduce influence of the noise, so increase reliability of the neural network training and prediction of signals for driving assistance.

Four different lane marker parameters, which have high correlation with a steering signal, are estimated and analyzed in the work: a) x coordinate variation at the fixed y coordinate x_v; b) angle α between the lane marker and the horizontal line at the fixed y coordinate; c) maximum $m_{x/y}$ of lane marker x and y coordinates ratio in a frame and d) curvature C. Below all four parameters are presented in more detail. It should be noted that all presented parameters are centered after their estimation.

3.1 Variation of *x* coordinate

The variation of x coordinate is estimated fixing y coordinated at a desired level. In the analysis of the x coordinate variation the desired y level was 500 pixels. For estimation of the lane marker x coordinate it is necessary to find line – lane marker intersection coordinate that is calculated solving a line – curve intersection equation. The problem geometry and coordinate system are shown in Fig. 1.

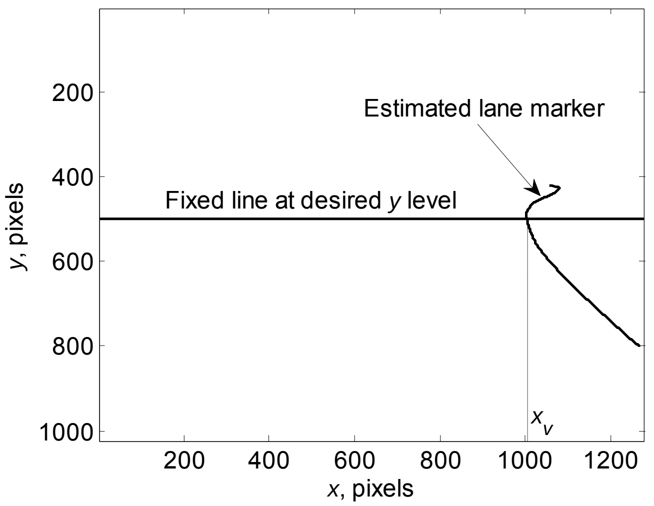

Fig. 1. *The coordinate system and the estimation of the x coordinate variation* x_v. *The proportions are true.*

It should be noted that origin of the coordinates system is the left upper corner of the image (Fig. 1).

3.2 Angle α

An angle α is the angle between the lane marker and horizontal line at desired y level (Fig. 2). The angle can be estimated in many ways. In the work it is evaluated from the law of cosines and the evaluation is presented below.

Let point A with the fixed coordinates (x_A, y_A) belongs to the horizontal line at desired y level y_A. Point B, having the coordinates (x_v, y_v), is the lane marker – line intersection point, i.e. the same point as in Fig. 1. Let point C also is the lane marker – line intersection point at desired y level y_C, so the coordinates are (x_C, y_C). In the work the difference between the y_A and y_B coordinates was selected to be 50 pixels. Knowing the coordinates of all three points, the angle α is expressed in the following way:

$$\alpha = -\arccos\frac{a^2 + b^2 - c^2}{2ab}, \tag{1}$$

where the quantities a, b and c are given in the following expressions:

$$a = \sqrt{(x_A - x_v)^2 + (y_A - y_v)^2}, \tag{2}$$

$$b = \sqrt{(x_v - x_C)^2 + (y_v - y_C)^2}, \tag{3}$$

$$c = \sqrt{(x_A - x_C)^2 + (y_A - y_C)^2}. \tag{4}$$

The angle α is inverted (Eq. 1) that it appears of the same sign as the steering signal. It should be noted that the lane marker part, limited by two horizontal lines at the desired levels y_A and y_C, is approximated by a straight line BC (see Fig. 2).

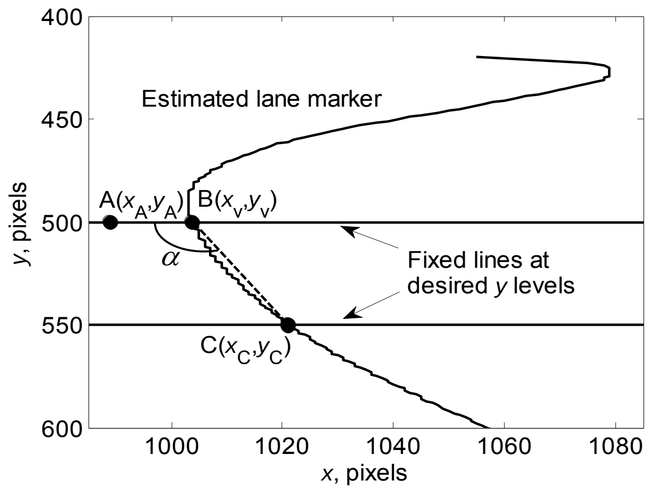

Fig. 2. *The angle α and the geometry for estimation of the angle. The lane marker is the same as it is shown in Fig. 1, but includes only zoomed upper part.*

3.3 Maximum $m_{x/y}$

Let denote lane marker coordinate x and y ratio as:

$$r_{x/y} = \frac{x}{y}, \tag{5}$$

Taking maximum value of the ratio along the lane marker, the maximum $m_{x/y}$ is estimated:

$$m_{x/y} = \max\left(r_{x/y}\right). \tag{6}$$

3.4 Curvature

Curvature is one of the most frequently used parameters for characterization of lane marker on a road. Usually the curvature, given by a plane curve $C = (x(\underline{t}), y(t))$ is estimated from the following generalized expression [8]:

$$C = \frac{x'(t)y''(t) - x''(t)y'(t)}{\left(x'(t)^2 + y'(t)^2\right)^{3/2}}, \tag{7}$$

where apostrophes denote the first and the second order derivatives of the curve parameters, respectively. From the last expression is clearly seen that estimation of the curvature is numerically unstable, so in the driving data analysis the use of the generalized form of the expression is complicated. To overcome the numerical instability, the curvature was estimated by the method which is derivative free, what resulted in numerical stability. Below the derivation of the method is presented in detail.

Two vectors are perpendicular when their scalar product is 0. Let analyze two vectors given by the following coordinates: (x_1, y_1) and (x_2, y_2), (x', y') and (x, y), where the pairs of the coordinates denote beginning and end points of the two vectors, respectively. The geometry is shown in Fig. 3.

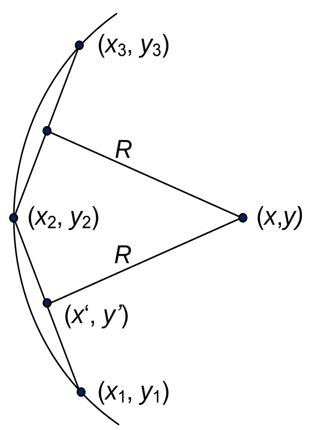

Fig. 3. *Geometry for curvature estimation. The first vector is given by the coordinates (x_1, y_1) and (x_2, y_2), the second one is denoted by the coordinates (x_2, y_2) and (x_3, y_3).*

The middle point, denoted by the coordinates (x', y'), of the first vector is given by:

$$x' = \frac{x_1 + x_2}{2}, \tag{8}$$

$$y' = \frac{y_1 + y_2}{2}. \tag{9}$$

For the two perpendicular vectors, given by the coordinates above (see Fig. 3), it can be written that their product is:

$$(x_2 - x_1)(x - x') + (y_2 - y_1)(y - y') = 0. \tag{10}$$

In the same way as before, the system of linear equations for two spans, given by the two vectors, (Fig. 3) can be written as:

$$\begin{cases} y = \dfrac{y_2 + y_1}{2} + \dfrac{x_2 - x_1}{y_1 - y_2}\left(x - \dfrac{x_2 + x_1}{2}\right) \\ y = \dfrac{y_3 + y_2}{2} + \dfrac{x_3 - x_2}{y_2 - y_3}\left(x - \dfrac{x_3 + x_2}{2}\right) \end{cases}. \tag{11}$$

After solving the Eq. 11, the coordinate x is expressed as:

$$x = \frac{\dfrac{x_2^2 - x_1^2}{y_2 - y_1} - \dfrac{x_3^2 - x_2^2}{y_3 - y_2} - (y_3 - y_1)}{2\left(\dfrac{x_2 - x_1}{y_2 - y_1} - \dfrac{x_3 - x_2}{y_3 - y_2}\right)}, \tag{12}$$

Assuming that y_2-y_1 = y_3-y_2 and the difference denoting as Δy, the last equation can be rewritten in the following form:

$$x = \frac{\left(x_2^2 - x_1^2\right) - \left(x_3^2 - x_2^2\right) - 2\Delta y}{2\left[\left(x_2 - x_1\right) - \left(x_3 - x_2\right)\right]}. \tag{13}$$

Due to estimation of the curve radius R (Fig. 3) it is necessary to evaluate y coordinate. The y coordinate can be calculated using Eq. 11 when x is substituted by the Eq. 12. However, for a parameter that is proportional to the curvature, it is enough to estimate the x coordinate. In this case the pseudo-curvature C can be written as:

$$C = \frac{1}{x}, \tag{14}$$

In the analysis x coordinates of lane markers were replaced by the ratio $r_{x/y}$ (Eq. 5) when the curvature C was investigated. The replacement was done due to unstable results when the raw x coordinates were used in the curvature analysis. In the work the curvature C was calculated applying Eq. 13 when the y_1 was 700 pixels, y_2 was 600 pixels and y_3 being 500 pixels. It is important to notice that for curvature detection, as well as for the rest of parameters mentioned here, it is enough to estimate the lane marker in the range of 500 – 700 pixels respective to the y axis. So in this case time for processing of images can be reduced significantly and all four presented lane marker parameters can be estimated.

4 Results of parameters estimation

To determine quality of the presented parameters, cross-correlation coefficients were calculated between the parameters and the steering signal. The results are listed in Table 1 which includes the results for 20 sets of driving data. In Table 1 the following notation was introduced: N_s is the number of samples in data set, θ_{min} and θ_{max} are the minimum and the maximum amplitudes of the steering signal in degrees, respectively. ρ_C, ρ_x, ρ_α and ρ_m are the cross-correlation coefficients between the vehicle's steering signal and the lane marker parameters: curvature C, x coordinate variation x_v, angle α and maximum $m_{x/y}$. Video data was recorded at 25 Hz sampling rate in 2006 and 2008 years. 20 Hz sampling rate was used in records of 2007 year. The driving data sets 1-5 and 6-10 were recorded on the same route, but by two different drivers. The results show (Table 1) that the cross-correlation coefficients are lower for the data recorded by the second driver (driving sets 6-10) comparing them to the results of the first driver (driving sets 1-5). That can be explained by different traffic scenario (i.e. lead vehicles and etc.) and individual driver's behavior (experience and driver's adaptation to the car).

The results clearly show that in some cases the cross-correlation coefficients are significantly below 0.9. Major part of these low correlation values was caused by missing lane marker due to side streets or lane marker deterioration. In the work the gaps in the parameters were interpolated by cubic splines.

Table 1. *The estimated cross-correlation coefficients between the presented parameters and the vehicle's steering signals.*

No.	Year	N_s	ρ_C	ρ_x	ρ_α	ρ_m	θ_{min} / θ_{max}
1	2006	1600	0.89	0.92	0.76	0.89	-21 / 21
2			0.93	0.94	0.95	0.88	-17.5 / 14
3			0.85	0.96	0.93	0.83	-19.25 / 101.5
4			0.76	0.87	0.75	0.83	-42 / 101.5
5		1106	0.77	0.85	0.56	0.81	-42 / 29.75
6		1600	0.91	0.93	0.81	0.91	-21 / 15.75
7			0.86	0.86	0.66	0.9	-15.75 / 15.75
8			0.38	0.74	0.59	0.76	-21 /12.25
9			0.92	0.98	0.94	0.93	-43.75 / 108.5
10		1292	0.92	0.95	0.86	0.96	-47.25 / 29.75
11	2007	897	0.97	0.98	0.87	0.91	-31.5 / 15.75
12		1600	0.97	0.97	0.90	0.88	-22.75 / 19.25
13		1251	0.96	0.93	0.85	0.86	-22.75 / 21
14		1291	0.91	0.83	0.83	0.59	-17.5 / 8.75
15		1600	0.85	0.92	0.78	0.83	-40.25 / 22.75
16			0.98	0.98	0.89	0.88	-35 / 44
17		1366	0.85	0.92	0.78	0.83	-12.75 / 7.5
18	2008	1361	0.89	0.93	0.80	0.76	-22 / 10.75
19		851	0.93	0.93	0.92	0.90	-21 /17.5
20		1020	0.92	0.97	0.94	0.95	-36.75 / 33.25

Summarizing the results, listed in Table 1, one can see that the highest correlations (0.98) can be estimated between the steering signal and the lane marker curvature or / and x coordinate variation at the desired y coordinate level. The cross-correlation coefficients between the steering signals and the parameters (angle α and maximum $m_{x/y}$) were a bit lower than in previous case and they did not pass 0.95 and 0.96 levels, respectively.

Illustrations of the estimated parameters are presented in Figs. 4 – 11. The Figs. 4 – 7 correspond to the data set No. 16 and Figs. 8 – 11 show the results of the data set No. 19. Each signal, the steering and the parameter, are centered and normalized by a maximum of amplitude separately. The illustrations clearly show that in most cases the steering signal is delayed comparing it to the lane marker parameters, that aids driver's steering signal prediction.

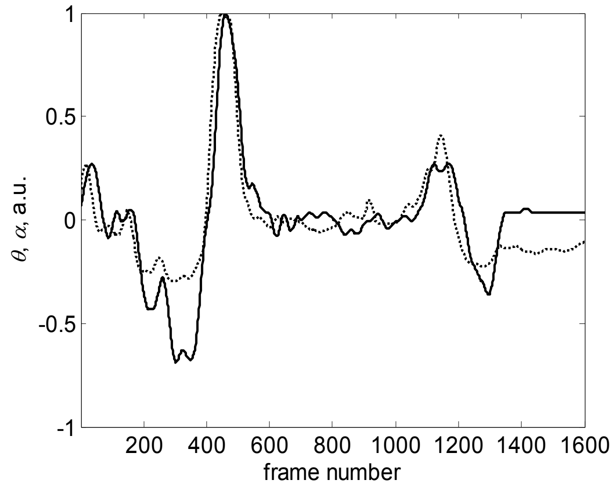

Fig. 4. *The steering signal θ (solid curve) and the angle α (dotted curve). The data set No. 16. a.u. stands for the arbitrary units.*

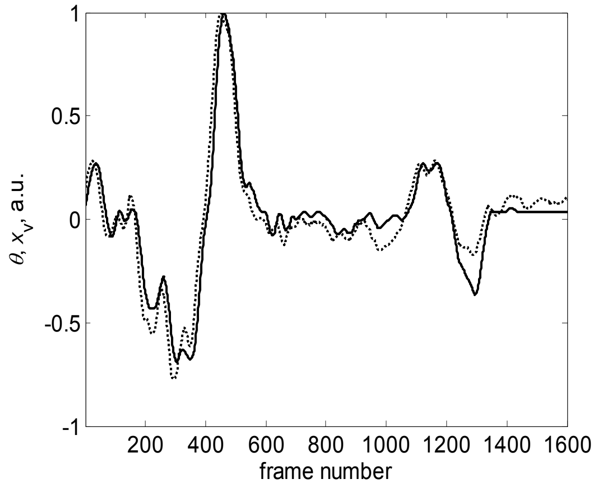

Fig. 5. *The steering signal (solid curve) and the variation of the lane marker coordinate x (dotted curve) when y = 500 pixels. The data set No. 16.*

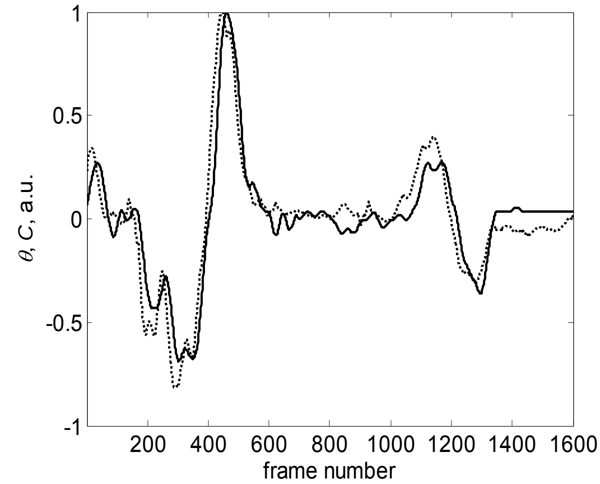

Fig. 6. *The steering signal (solid curve) and the curvature C (dotted curve). The data set No. 16.*

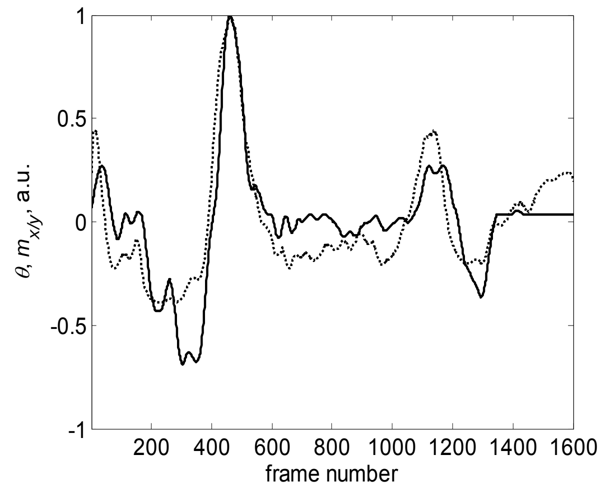

Fig. 7. *The steering signal (solid curve) and the maximum of the lane marker coordinates x and y ratio (dotted curve). The data set No. 16.*

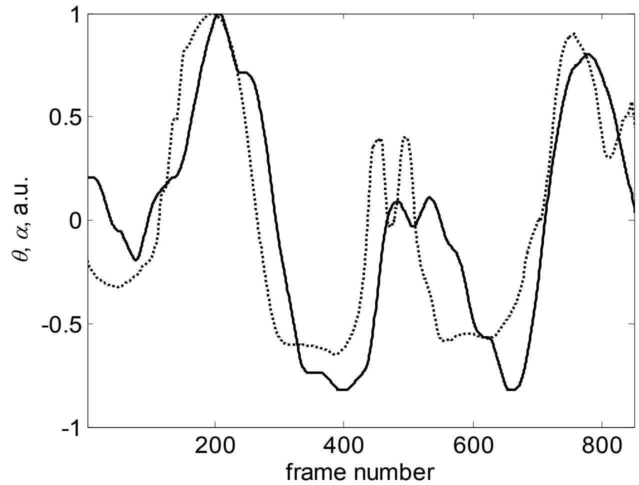

Fig. 8. *The same as in Fig. 4, but for the data set No. 19.*

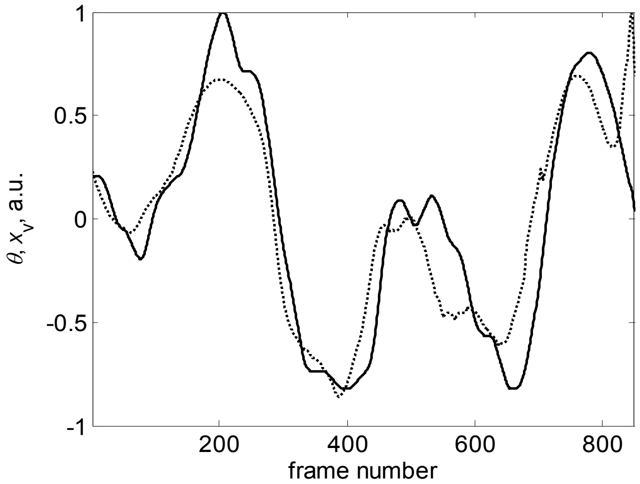

Fig. 9. *The same as in Fig. 5, but for the data set No. 19.*

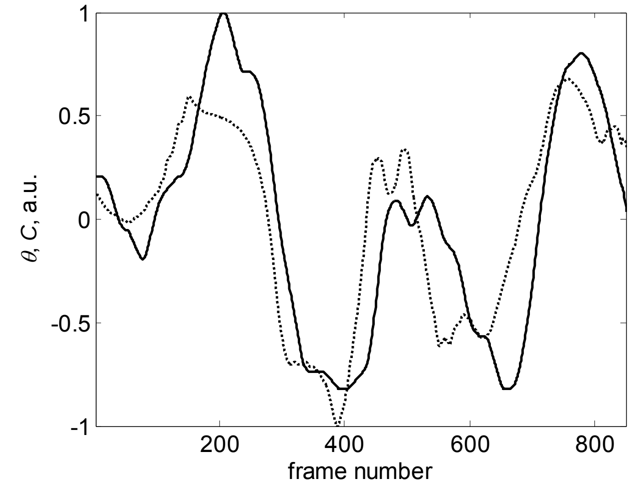

Fig. 10. *The same as in Fig. 6, but for the data set No. 19.*

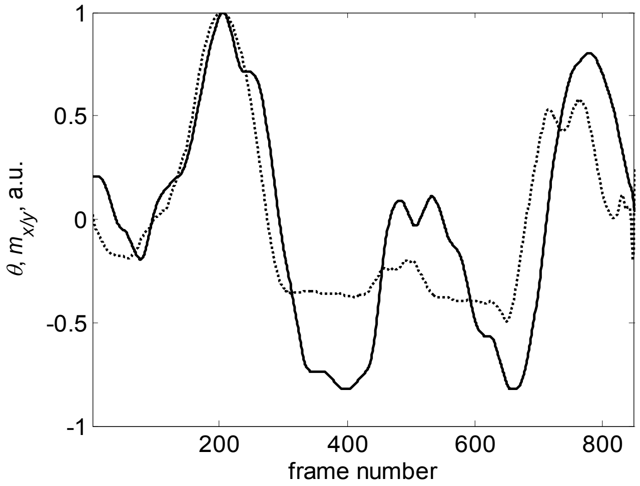

Fig. 11. *The same as in Fig. 7, but for the data set No. 19.*

The time delays between the signals, presented in Figs. 4–11, are calculated taking maximum of the cross-correlation functions between them. The steering signal was selected as the reference. The results are listed in Table 2, where τ is the time delay in seconds. One can observe that the parameters precede the steering signal from 0.5 s to 1.12 s in this case and the delays are not stable. It is important to notice that an elimination of the time delay between the steering signal and a feature, used for neural network training, reduces the steering signal prediction error [7]. The time delay can be compensated numerically estimating lane marker parameters at different y coordinate levels. The compensation of the time delay would increase the cross-correlation between the signals.

Table 2. *The time delays between the steering signal and the parameters.*

No.	τ_C, s	τ_x, s	τ_α, s	τ_m, s
16	-0.7	-0.5	-0.65	-0.7
19	-1.12	-0.64	-1	-0.88

5 Steering prediction with neural network

The four visually-based parameters were tested for potential to predict a vehicle's steering signal. In the investigation the steering signal was predicted for a specific driver; therefore data recorded by the same driver were analyzed. It is important to notice that the data, which are used for prediction of steering signal, should be recorded by the same driver, because each individual driver has his own style of vehicle's driving.

The analyzed data were recorded on the country road in Germany in 2006. It should be noted that some part of the driving data also was recorded in a suburb, where street lane extraction is more difficult, and the steering is more complicated to predict. The steering angle varied in the range from -50° to 50° in both directions: left and right (see Fig. 12). The signal, presented in Fig. 12, was composed from data sets No. 6-10 (see Table 1) consecutively joining the recorded signals. The estimated visually-based parameters were joined in the same way as the steering signal and they are presented in Fig. 13.

Different methods are used for predictions of time sequences. In the field of driving assistance systems or analysis of driving data the following numerical methods are used: neural networks [9], fuzzy logic [10, 11], Markov chains [12-14] and etc. In the work the steering angle was predicted using two-layered neural network. There were 2 neurons in the hidden layer with a sigmoid transfer function. The predicted signal value was averaged from 10 initializations. The averaging increased the signal to noise ratio.

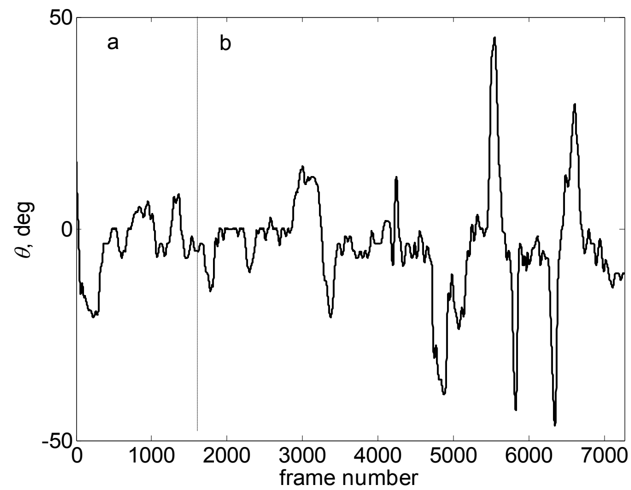

Fig. 12. *Steering signal for prediction with neural network: a) steering signal for neural network testing, b) steering signal for neural network training.*

The steering data used for neural network learning (Fig. 12b) varied approximately from -50° to 50° and for testing the signal varied in the range from -24° to 10° (Fig. 12a). The test signal had lower amplitude as compared to the training signal.

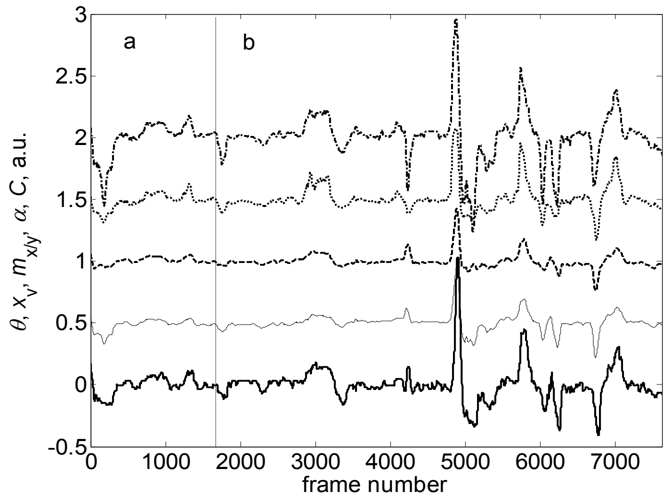

Fig. 13. *Parameters for steering signal prediction with neural network: a) data for neural network testing, b) data for neural network training, where the solid thick line is the true steering signal, the solid thin line corresponds to the x_v parameter, the dashed line denotes the $m_{x/y}$ parameter, the dotted line denotes the parameter α and the dashed-dotted line denotes the parameter C.*

The steering signal was predicted with each visually-based parameter and all their possible combinations. The parameter combinations used for the neural network training and testing are listed in Table 3. Estimated mean squared errors (MSE) of the predicted steering signal obtained with these parameter combinations also are listed in Table 3.

Table 3. *Parameter combinations for the steering signal prediction and calculated MSE of the predicted steering signal with the corresponding parameter set at input.*

No.	*Parameter combinations*	*MSE, %*
1	x_v	4.50
2	$m_{x/y}$	3.33
3	α	3.66
4	C	3.10
5	x_v, $m_{x/y}$	3.30
6	x_v, α	4.24
7	x_v, C	4.23
8	$m_{x/y}$, α	3.05
9	$m_{x/y}$, C	2.87
10	α, C	3.29
11	x_v, $m_{x/y}$, α	3.00
12	x_v, $m_{x/y}$, C	3.01
13	x_v, α, C	4.15
14	$m_{x/y}$, α, C	2.93
15	x_v, $m_{x/y}$, α, C	3.07

At first, all four visually-based parameters were tested separately. The best performance, i.e. the smallest prediction error, was reached when the parameter C (curvature) was used as the input for the neural network (Fig. 14d). Both parameters $m_{x/y}$ (maximum of x and y coordinated ratio) and α (angle between the lane marker and the horizontal line at the desired y level) showed a bit larger prediction error than curvature (see Fig. 14b. and Fig 14c, respectively). During analysis of the single parameters the biggest error value was obtained when the parameter x_v (lane marker x coordinate variation at the desired y level) was used as the input for the neural network (Fig. 14a).

The visually-based parameters were tested in pairs as well. The smallest MSE between the true and the predicted steering signal was obtained when the parameters $m_{x/y}$ and C were used for the neural network input (Fig. 15c). Parameter sets $m_{x/y}$ and α (Fig. 15b), x_v and $m_{x/y}$ (Fig. 14e), α and C (Fig. 15d) were a bit worse, respectively. Combinations of the x_v and α (Fig. 14f), x_v and C (Fig. 15a) signals resulted in the largest MSE in the pair combinations.

It is clearly seen that a triplet of the parameters gave one of the smallest MSE value (Table 3). The best performance was observed when the parameters set, consisting of the $m_{x/y}$, α and C signals, was used for the neural network examination. In this case the results are presented in Fig. 16b. The worst steering signal prediction result was obtained when the triplet composed of the x_v, α and C signals was applied for the neural network training and testing (see Fig. 16a).

A general case, when all four parameters simultaneously were used for the neural network training and testing, has shown one of the best performance (see Table 3 for details). The illustration of the prediction result is provided in Fig. 16c.

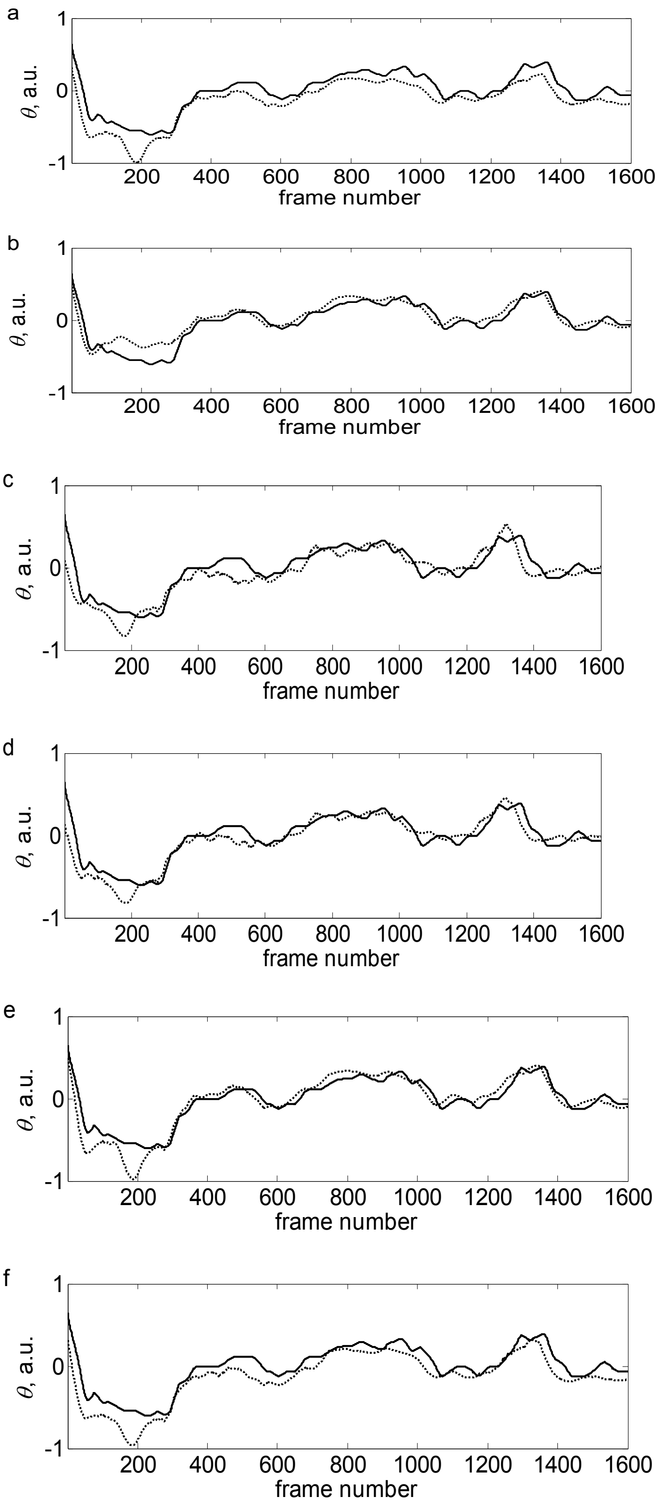

Fig. 14. *Steering signal predictions with the neural network when the following network inputs were used: a) x_v; b) $m_{x/y}$; c) α; d) C; e) x_v and $m_{x/y}$; f) x_v and α. In the illustrations the solid curve marks the true steering signal and the dotted curve marks the predicted steering signal.*

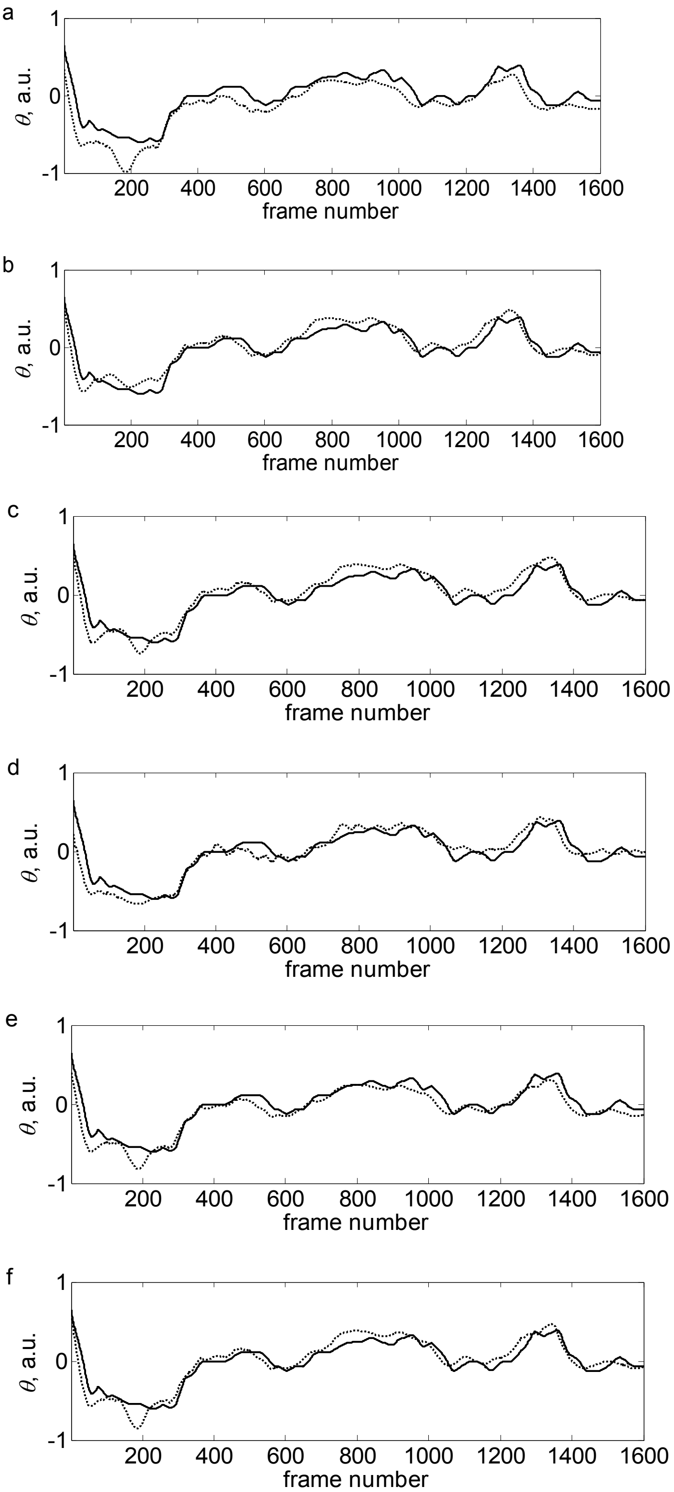

Fig. 15. *Steering signal predictions with the neural network when the following network inputs were used: a) x_v and C; b) $m_{x/y}$, and α; c) $m_{x/y}$ and C; d) α and C; e) x_v, $m_{x/y}$ and α; f) x_v, $m_{x/y}$ and C. The solid curve corresponds to the original steering signal, the dotted curve marks the predicted steering signal.*

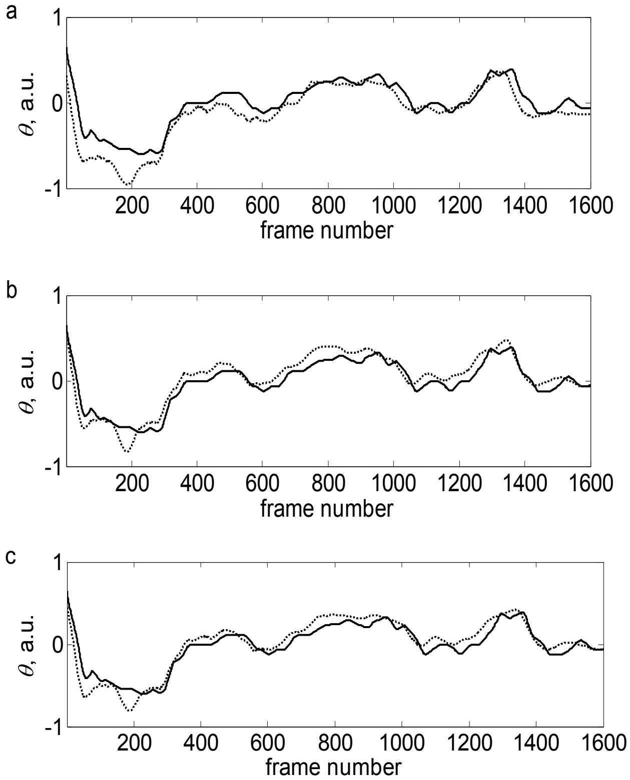

Fig. 16. *Steering signal predictions with the neural network when the following network inputs were used: a) x_v, α and C; b) $m_{x/y}$, α and C; c) x_v, $m_{x/y}$, α and C. The solid and dotted curves mark the original and predicted steering signals, respectively.*

A vehicle's velocity signal *v* from CAN-bus data was included in the analysis in addition to pure visually-based parameters for the steering signal prediction. The estimated results showed that the MSE was larger in comparison with the same parameter set without the velocity signal. Some illustrative cases are listed in Table 4.

Table 4. *MSE values for parameter sets with the smallest prediction MSE value, with added velocity signal v and without it.*

Parameter set	MSE, %	*Parameter set + v MSE, %*
$m_{x/y}$, C	2.87	2.90
$m_{x/y}$, α, C	2.93	3.14
x_v, $m_{x/y}$, α	3.00	4.04
x_v, $m_{x/y}$, C	3.01	3.35

As it is seen from the results, the velocity of the vehicle very little influences steering signal prediction results, but the results always become worse when velocity is added. This might happen because the parameters extracted from visual data are sufficient to predict a steering signal in the data set that is used in this study, and additional parameters only lead to over-fitting.

The predicted signal is usually shifted to the left from the true steering signal. That can occur due to the driver's reaction time. The parameters are taken from the right lane, and they are objective. According to the study [15] a driver needs 0.5 s to take actions when a new or unexpected situation occurs.

An experiment was made to find out (ascertain) when the predicted signal best corresponds to the true signal. The combination of the visually-based parameters which produced the smallest MSE was used in the investigation (see Table 3). The predicted signal was shifted to the right every 0.04 s, for the overall 1 s interval. The MSE between the predicted and the true signal was calculated at each shift. The estimated smooth MSE variation is presented in Fig. 17 which clearly shows that optimum exists where the smallest prediction error is obtained. The results show that the smallest MSE was reached at 0.5-0.6 *s*. Summarizing the results, it can be concluded that taking into account driver's reaction time factor the MSE can be reduced from 2.87% to 2%. The illustration of the predicted steering signal shift is presented in Fig. 18.

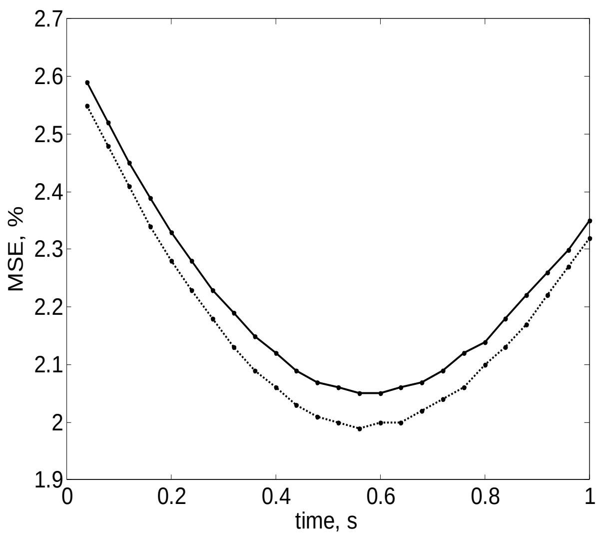

Fig. 17. *MSE between the predicted and the true steering signals when the predicted signal is shifted to the right every 0.04 s. The solid line shows the $m_{x/y}$ and C parameters set, the dotted line corresponds to the $m_{x/y}$, α, C signals combination.*

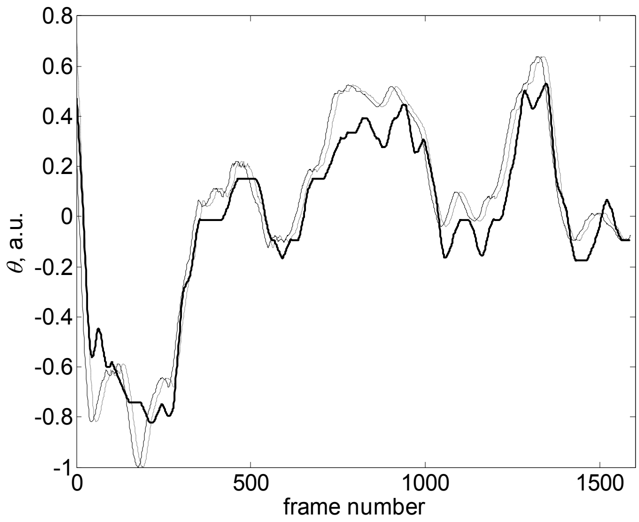

Fig. 18. *Time-shifting of the predicted signal. The true signal is marked by the solid line, the dashed line represents the predicted signal and the predicted signal after shifting by 0.56 s is marked by the dotted line.*

5 Discussion and feature works

In the work four different lane marker parameters with high correlation to vehicle's steering signal are presented. The parameters can be supplemented with additional lane marker parameter that is not presented in the analysis – the curve's area. In our previous work it was estimated that the curve area also has high correlation with a steering signal [6].

It is important to notice that the lane marker parameters were estimated from the mono-camera images without use of any undistortion processing for the images which is used to compensate video cameras distortions in the images [16]. Moreover, in the presented analysis it was shown that there is no need to use stereo cameras for lane marker estimation and parameters extraction. Therefore evaluation of the parameters is simple and not time consuming process, so the presented lane marker parameters can be reliably estimated in real time applications.

The data used for the neural network learning was unprocessed; it included two over-takings and many over-steering situations. Despite these circumstances, the two-layered neural network with 2 neurons in the hidden layer and sigmoidal transfer function was able to learn the correct behavior and predict the steering signal with more than 95% accuracy.

Next, different drivers behavior on the same road will be analyzed and predicted. The study on common driving rules and individual steering differences will be performed.

In future steering signal prediction applying the presented parameters, and using neural network techniques will be developed and implemented into hardware for driving assistance.

6 Conclusions

The four different lane marker parameters with high correlation to the vehicle's steering signal have been estimated and evaluated from mono-camera images. It has been shown that the very high correlation (up to 0.98) between the presented lane marker parameters and the vehicle's steering signal can be achieved.

The simple and derivative free method for estimation of lane marker curvature from mono-camera images has been presented.

It has been shown that it is possible to predict a steering signal with mean squared error less than 5% when the neural networks, used in the predictions, are trained by the visually-based parameters. Predicted signal shifting to the right (attributed to the driver reaction delay of 0.5 s) can reduce the error further.

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