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SYSTEM FOR DETECTING VEHICLE FEATURES FROM LOW QUALITY DATA

ABSTRACT

The paper presents a system that recognizes the make, colour and type of the vehicle. The classification has been performed using low quality data from real-traffic measurement devices. For detecting vehicles' specific features three methods have been developed. They employ several image and signal recognition techniques, e.g. Mamdani Fuzzy Inference System for colour recognition or Scale Invariant Features Transform for make identification. The obtained results are very promising, especially because only on-site equipment, not dedicated for such application, has been employed. In case of car type, the proposed system has better performance than commonly used inductive loops. Extensive information about the vehicle can be used in many fields of Intelligent Transport Systems, especially for traffic supervision.

KEY WORDS

vehicle type detection; vehicle make detection; vehicle colour detection; real traffic data;

1. INTRODUCTION

Every year the intensity of road traffic is constantly growing along with the increasing number of offences and traffic accidents. The services responsible for maintaining road order and safety require assistance in the form of automatic vehicle detection. With such dense traffic stream, the information about the car license plate only is usually insufficient, despite the popularity of such systems [1, 2]. An example is the Weighting In Motion (WIM) system, where relevant services are patrolling the route at a short distance from the measurement point. Obtaining data about the vehicle colour, make and category is crucial for a fast intervention and preventing damages to road infrastructure.

Many systems for visual analysis of car appearance have been proposed recently. Most of them are focused on recognizing only one of the mentioned features [3, 4, 5]. On the other hand more complex expert systems, designed to provide comprehensive information about the vehicle, have also been presented [6, 7, 8].

Vehicle type recognition is usually performed on the basis of registered images [9, 10]. Such solutions are computationally demanding, which implies a need to install more efficient and more expensive hardware on the monitoring site. A different approach, most common in practical applications, is vehicle category detection using inductive loops and recognizing the car type on the basis of the number of axes using proper algorithms [11, 12]. Inductive loops have to be installed in the road pavement and periodically serviced causing traffic jams. Most of the make recognition systems employ feature extraction and classification methods.

Commonly used feature extraction algorithms are: methods based on contour information [13], Canny edge detector [14], square mapped gradients [15], Curvelet Transform [16], Speeded-Up Robust Features (SURF) [6, 3] and Scale Invariant Feature Transform (SIFT) [6, 17]. For classification purposes Support Vector Machines – SVM [16, 18], Bayesian methods [4, 19] or neural networks [20] are the most popular tools. There are, however, some limitations of the presented systems. The first one concerns the image quality. The authors of [4] used pictures of cars parked near the camera. Another problem is a small number of vehicle models in the database. In [6] a database of 17 different models has been used while the system presented by [21] recognizes among only 10 makes and models.

Solutions for vehicle colour recognition differ in the colour space that is analyzed and the processing algorithm. In [22] a two-step process has been developed. First, the background is removed using the foreground mask. Then, the colour is recognized by a SVM classifier with a two-layer structure. The same classifier (SVM) is used by [23] for recognizing among five colours in HSV colour space (Hue, Saturation, Value), whereas [24] concentrated on HSI (Hue, Saturation, Intensity) colour space. A more complex approach is presented by [25], where the Grid Kernel has been proposed.

The aim of this study was to design a system for automatic detection of vehicle specific features (type, make and colour) from low quality data for real-time traffic supervision. Since the registered images and signals have been acquired using different measurement devices, various methods for detecting each feature have been employed. The colour recognition approach is based on a fuzzy system, which is able to distinguish 10 colours. The make classification employs the SIFT method for feature extraction with no limit for the number of classes. The vehicle type recognition has been performed on one dimensional data yielding a more robust algorithm than image-based approaches.

This paper is an extension of [26] and [27], where the preliminary studies results for vehicle make and colour detection have been presented. In this study the image processing stage for reliable car brand pattern detection has been revised and improved mainly by the redevelopment of the car brand segmentation and classification algorithms. The brand segmentation involves vehicle lights extraction along with texture analysis. The classifier relies mainly on the information about the image compatibility with reference patterns. Moreover, a more comprehensive evaluation and analysis have been performed using car images including 46 car makes and 10 colours. Special attention has been paid to the influence of the value of the SIFT distance ratio r_d value on recognition efficiency. The vehicle type detection on the basis of one-dimensional signal registered with laser distance meter is also a novel part of the presented work.

The paper is organized as follows. Section 2 presents the measurement system and the data set used in the research. The algorithms for detecting vehicle type, colour and make are described in Section 3. Section 4 contains the results and Section 5 draws the conclusion.

2. DATA

The detection of vehicle specific features has been performed on the basis of data registered on WIM stations, which have been equipped with the following devices:

- Noptel CM3-30 laser distance meter for acquiring vehicle height (sampling frequency 1 kHz),
- colour camera with image resolution of 640×480 for registering colour images of vehicles,
- camera, a part of the Automatic Number Plate Recognition (ANPR) system, taking pictures of vehicle fronts with the resolution of 752×480.

All devices have been mounted above the road line as shown in *Figure 1*. The image registration is triggered when a vehicle passes the inductive loops embedded in the road surface. The laser sensor starts recording when the measured vehicle height exceeds the predefined threshold (50 cm) and stops when the height drops to zero.

More than 2,000 objects of each data type have been recorded. *Figure 2* presents an exemplary set of registered data which includes the colour camera picture (*Figure 2a*), the ANPR camera picture (*Figure 2b*) and the vehicle height vector, consisting of height values registered using the laser distance meter with the time step of 1 ms (*Figure 2c*).

Preliminary studies have indicated that the colour camera resolution is too low to detect the car manufacturer, and the camera of ANPR system does not provide colour images. Therefore, two cameras had to be employed.

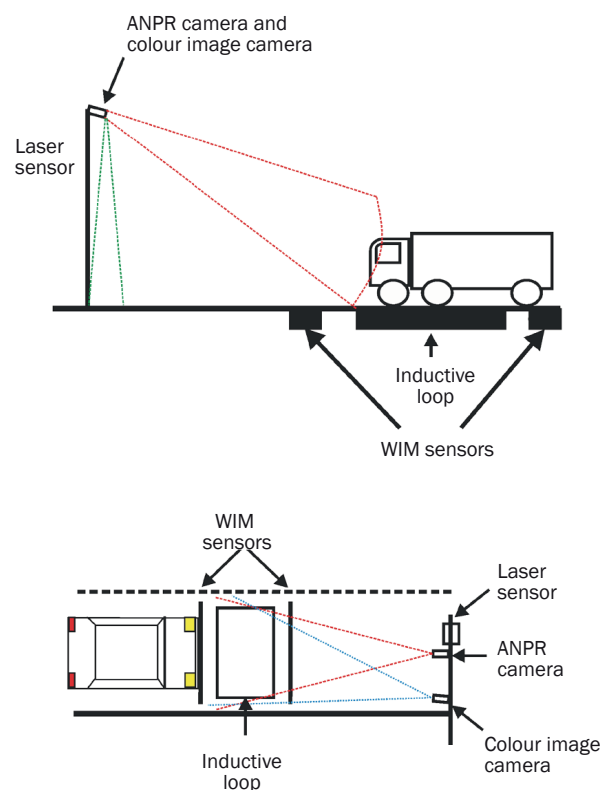


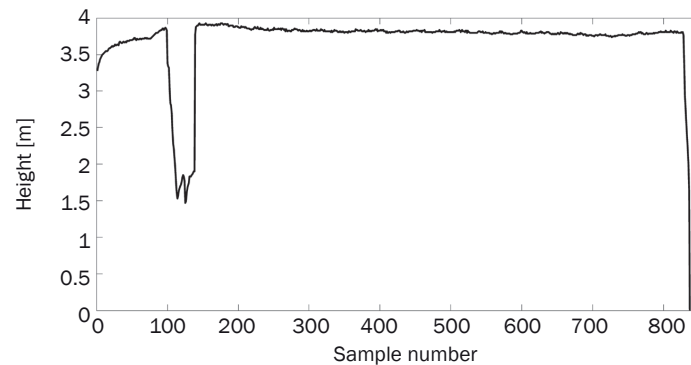
Figure 1 - Configuration of data acquisition devices



a) Image from the colour camera for vehicle colour detection



b) Image from the ANPR camera for make detection



c) Vehicle height vector registered with the laser distance meter

Figure 2 – Data examples

3. METHODS

3.1 Vehicle type detection

Vehicle category detection has been performed on the basis of the European Specification COST 323 [11], which defines eight categories of vehicles: 1 - car and light trailer (gross-weight < 3.5t), 2 - two-axle rigid lorry, 3 - more than two-axle rigid lorry, 4 - tractor with semi-trailer supported by single or tandem axles, 5 - tractor with semi-trailer supported by tridem axles, 6 - lorry with trailer, 7 - bus, 8 - other vehicles. Since categories 2 and 3 are distinguishable only on the basis of axle number and this parameter cannot be measured with a distance meter, these two categories have been joined into one (denoted in paper as 23). The same applies to categories 4 and 5, which have built category 45.

The laser distance meter provides a vector of vehicle height VH that represents the vehicle contour. Based on the registered vehicle contour the following vehicle features have been extracted:

- the mean, maximum and variance of the vehicle height,
- vehicle length,
- the existence and position of the contour indentation, representing the indentation between the tractor and its semi-trailer (category 45) or between lorry and trailer (category 6).

Figure 3 presents a graphical illustration of the evaluated parameters.

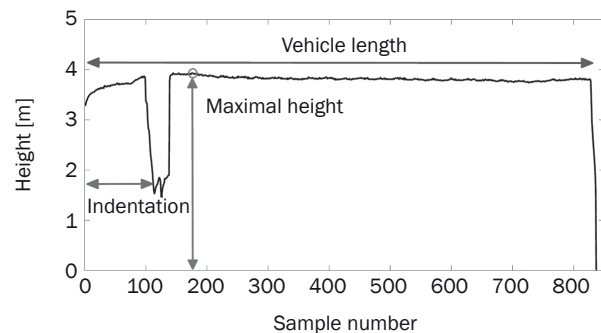


Figure 3 – An illustration of vehicle contour features

Vehicle height VH_m is determined by:

$$VH_m = \max(VH) \quad (1)$$

The variance of vehicle height (s_{VH}^2) has been computed in order to distinguish between lorries and buses. The idea, which was behind the calculation of the variance, resulted from the observation that the height of the bus roof varies to a very small extent, in contrast to the truck where the cabin and trailer have different heights. In addition, there is a gap between the cabin and the trailer, which also increases the value of the variance. The first and last 10% of samples of the height vector are not included in the variance

calculation, because they contain information about the front and the rear of the vehicle, where the height is changing rapidly, which greatly affects the resulting variance. The number of excluded samples has been chosen empirically.

The sampling frequency of height measurement is given (here $f=1,000$ Hz) and the distance $D(f,v)$ covered by the vehicle between each measurement can be calculated as:

$$D(f,v) = 3.6^{-1} \cdot 10^{-3} f^{-1} \cdot v \tag{2}$$

where: v – is the vehicle velocity in km/h.

The vehicle velocity has been provided by the inductive loop, since it has been available on the WIM site. In the final solution two laser distance meters can estimate the velocity as well.

Vehicle length is estimated using the position of the last non-zero value in the vehicle height vector – IE (Index End). Then, the vehicle length – L (in metres) is obtained from the formula:

$$L = D(f,v) \cdot IE \tag{3}$$

For categories 45 and 6 the indentation between the first and the second unit of the vehicle has been calculated. For category 45 it is the end of the cabin and for category 6 it is the gap between the lorry and the trailer. The vehicle contour signal has been filtered in order to reduce the noise. The indentation position has been determined by the index of the first value that is lower than the half of the vehicle height (II Index Indentation):

$$II = \min(I): \{VH(I) < 0.5 \cdot VH_m\} \tag{4}$$

The value of II has been selected empirically. In order to suppress the distortion, the middle value between the maximum vehicle height and the ground has been chosen. This feature distinguishes between categories 45 and 6. For categories 1, 23 and 7, the value of II equals L .

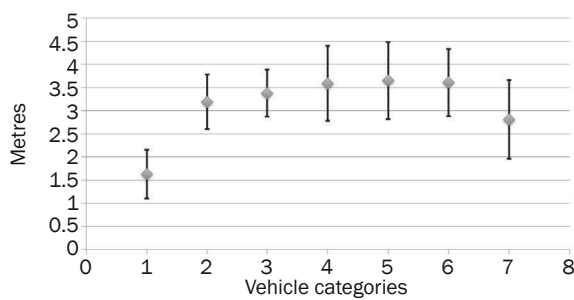
Category classification algorithm

Sample data have been analyzed and the distribution of the extracted shape features values has been calculated. The results of height, length and position of the 1st unit are shown in *Figure 4*. Central points represent mean features values and the whiskers mark the double standard deviation.

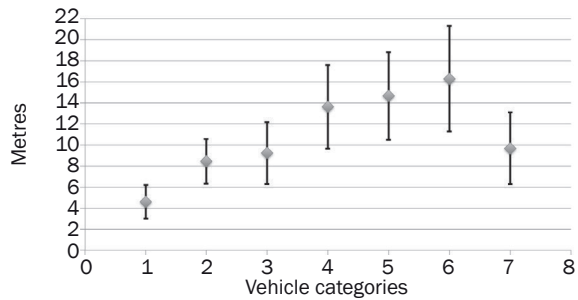
On the basis of the analysis of the obtained results, a set of rules for classification purposes has been developed (*Table 1*).

Table 1 – Vehicle category classification rules

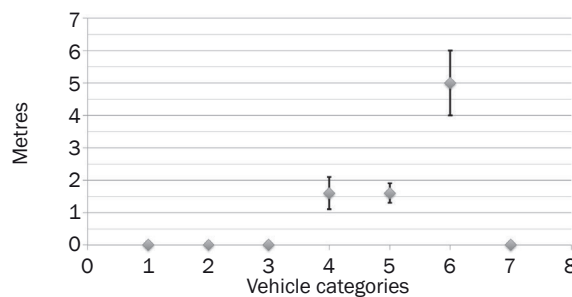
Category	VH_m [m]	L [m]	II [m]	s_{VH}^2
1	<2.5	<6	-	-
23	>2.5	6.0 - 12.0	-	>75
45	>2.5	>12.0	<3.5	>75
6	>2.5	>12.0	>3.5	>75
7	>2.0	6.0 - 12.0	-	<75



a) Height



b) Length



c) Indentation

Figure 4 – Distributions of shape features for each category

3.2 Vehicle colour detection

The vehicle's colour should be a member of a closed colour group, consisting of ten hues. These are: white, grey, black, red, brown, orange, yellow, green, blue and purple. The colour detection algorithm has been created on the basis of the regulation of the Polish Ministry of Transport for car colours.

The proposed methodology contains three stages: car segmentation, region of interest (ROI) detection and colour recognition.

Segmentation

The car segmentation procedure detects the vehicle foreground from all cars visible in the image (Figure 5a). To solve this problem a grey scale image is analysed. The procedure is based on the car shadow detection. As a shadow the darkest pixels (pixels with the lowest intensity value) in the image are considered (Figure 5b). Since these pixels are located under the car, their shape and position are independent on light conditions, which has been checked on pictures taken at different times of the day. What is more, the horizontal part of the shadow is sufficient to prevent mistakes for long vehicles.

Very often the number of areas that satisfy the mentioned condition, is greater than one. Therefore, a correction is required. It relies on a selection of the largest darkest area located in the lower left corner of the image (extreme left-hand lane). A preliminary study confirms that in more than 98% of the cases the front shadow of the car is obtained. What is more, the width w of the shadow corresponds to the car width. (Figure 5c). On the basis of that knowledge, a rectangular region of interest is built (Figure 5d). Since the

typical car aspect ratio (i.e. width: height) equals 4:3, the lengths of the rectangle sides are $height = \frac{width}{3}$. This rule also works correctly for vans and trucks, since the region contains a significant part of the coloured vehicle elements.

ROI detection

The car segmentation procedure is followed by the extraction of the region of interest (ROI) (Figure 6a). On its basis an auxiliary image (Figure 6b) is created. It presents stripes with the standard deviation of image hue computed for each row of Figure 6a. Next, the stripe with the lowest standard deviation value is selected. It forms the area/zone that reflects the car colour (Figure 6c).

Colour recognition

The procedure of colour recognition works in the HSV colour space. These three components are the input data for Mamdani Fuzzy Inference System (MFIS). The fuzzy system has been described in details in [27].

3.3 Vehicle make detection

The automatic make recognition system has been developed for the detection of specific car makes based on low-contrast images of car fronts (Figure 7a). The algorithm consists of four stages: car brand segmentation, feature extraction, pattern matching and classification.

Car brand segmentation

Car brand segmentation begins with the license plate detection stage. The detection of the lights leads to the extraction of the ROI in-between and below

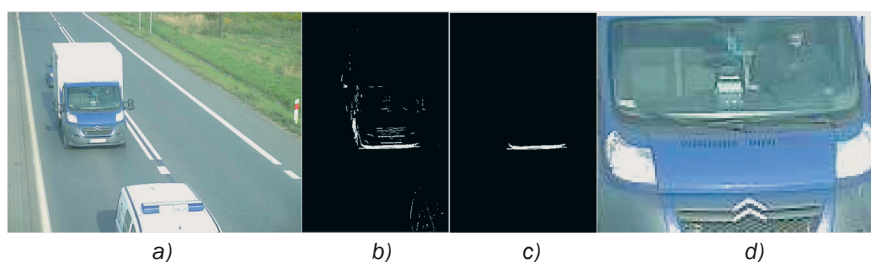


Figure 5 – Car segmentation stages

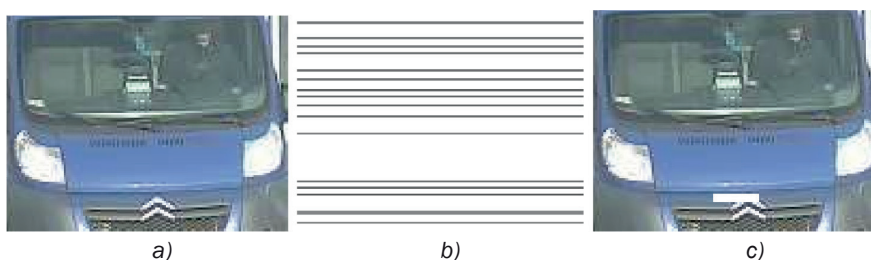


Figure 6 – Region of interest (ROI) detection stages

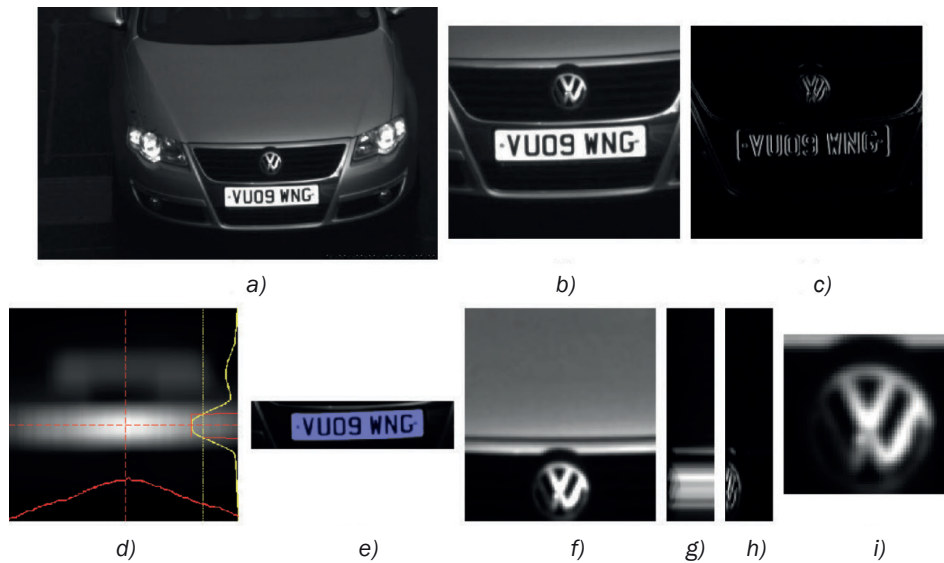


Figure 7 – Image pre-processing stages

a) original image; b) license plate ROI; c), d), e) selected illustrations of license plate detection stages; f) car brand ROI; g), h), i) selected illustrations of car brand detection stages

(Figure 7b). The ROI is analyzed in terms of the texture features in order to detect the plate region (Figure 7c-e). The image is then rotated to position the plate parallel to the image horizontal axis. A region above the license plate is extracted for the car make symbol detection (Figure 7f).

A few assumptions have been made: (1) the brand is supposed to be located on the ROI vertical axis of symmetry; (2) it should feature high spatial frequency components; (3) due to its symmetry the extraction relies mainly on horizontal gradient features (Figures 7g and 7h). As a result, a small rectangle including the car brand is extracted and passed to the recognition stage (Figure 7i).

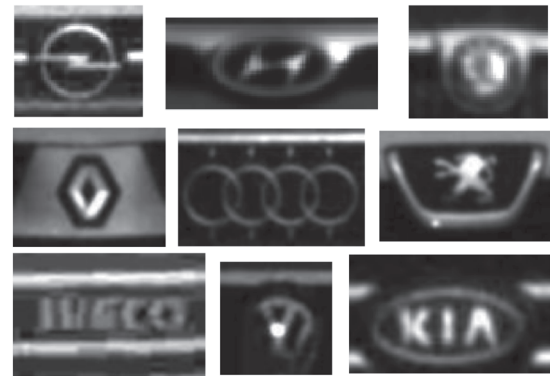


Figure 8 – Sample car brand ROI images

Feature extraction

For feature extraction the Scale Invariant Feature Transform (SIFT) has been used [28, 29]. It is based on key points – extrema within the image scale space [30, 31]. Each extracted key point is represented by its location, scale, orientation and a vector of textural descriptors. The key issue here is to choose the proper image/ROI as an input of the SIFT analysis. Due to the image character, contrast and compression method (JPEG), the car brand ROI as described above has been found as the best choice for the analysis (Figure 8). Moreover, the ROI is subjected to a slight Gaussian filtering, contrast enhancement and resampling, to normalize the length of the longer ROI side at 128 pixels. Such an image generates ca. 10-60 key points.

Pattern matching

Lowe's SIFT pattern matching relies on fitting the descriptor vectors by means of their Euclidean distance, all performed for each pair of key points. If the

distance between two points from various patterns is significantly small, they can be considered as being matched. To make the matching process fully automatic, a comparison between the closest and the second-closest key point is performed. If the distance ratio is lower than constant r_d value, then the match is approved.

Each extracted image is compared to reference patterns from the database, which consists of N_g groups (car makes) with N_{ppb} patterns per brand. Some makes have various, significantly different symbols for their car models (e.g. Fiat or Dacia): each separate symbol constitutes a unique group. Therefore, N_g is generally slightly greater than the number of supported car makes. The process of reference patterns selection investigates their high ability to match same-brand samples and their low false positive susceptibility. Comparison of the sample with the reference

database objects produces matching vector **M**, containing numbers of key points shared with subsequent reference patterns.

Classification

At the classification stage vector **M** is examined, matching the sample under consideration via a multi-rule inference system:

- 1) A brand with the highest average number of matches within a group is chosen.
- 2) If the above rule produces no sole winner, the individual pattern with the highest number of matching key points induces the decision.
- 3) If there is still no unique decision, the top of the best matching reference patterns list is inspected to indicate the best represented brand.
- 4) Unsuccessful classification using all three above rules generates the decision "unrecognised".

4. RESULTS

All proposed methods have been implemented in Matlab R2012b and tested using the dataset presented in Section 2. Each test image has been assigned to one category, one colour and one make. Next, the percentage of correctly classified vehicles has been computed.

Car type detection results have been presented in Table 2. It can be noticed that the proposed method, employing laser distance meter, gives higher accuracy of detecting particular types than the algorithm that uses inductive loop as the measuring device. The difference between the overall accuracy is about 5% and it is determined by the first category which includes the largest number of cases (cars of total gross weight < 3.5t). The presented approach (in terms of the number of the distinguished vehicle types) does not provide as many data about the vehicle as inductive loops, yet it is comparable with image-based solutions while it has a far lower computational complexity and is insensitive to weather conditions.

Table 2 – Car category recognition results

Category	No. of cases	Correct detection [%]	Loop correct detection [%]
1	2,417	99.92	97.97
23	106	82.08	65.09
45	264	98.86	71.21
6	31	83.87	51.61
7	16	75.00	56.25
Total	2,834	98.84	93.51

The colour recognition algorithm has been verified using a data set including 2,419 images. The database includes vehicles of different brands and types (passenger cars, vans, trucks and buses). The detailed results are presented in Table 3.

Table 3 – Car colour recognition results

Colour	No. of cases	Correct [%]	Mostly mistaken for
Brown	5	40	Grey
White	655	68.24	Grey
Grey	825	61.33	Blue
Black	67	0	Blue
Orange	54	25.93	Grey
Yellow	56	19.64	Green
Green	98	38.78	Blue
Blue	385	86.75	Grey
Purple	46	78.26	Grey
Red	228	60.53	Grey
Total	2,419	63.08	

Values included in Table 3 refer to the total assessment of both stages: ROI detection and colour recognition. The error of ROI detection procedure very often arises from identifying the windscreen as the body of the car, whereas the correct performance of MFIS has been often disturbed by improper light exposure. Studies and numerical simulations led to the observation that methods of colour detection have to consider the light direction. Even local analysis, within homogeneous stripes, does not provide efficiency higher than 60%. Moreover, the colour recognition procedure often yields a neighbour colour or a grey colour. The similarity is visible in pairs Grey-Blue, Black-Blue, Yellow-Green, Green-Blue (pairs are understood as real colour-recognized colour). Incorrectly detected colours are the significant components of the real or neighbour colours in the HSV colour palette, whereas the system reports grey colour when lighting conditions were poor or the analysed images were of very low quality.

Evaluation of the car segmentation procedure has been presented in [27] and reached 98%. It has been proven that the segmentation efficiency is independent on the type (short or long vehicles), brands and even light conditions (sunny or cloudy day).

The obtained results are comparable with those presented in [23], where also an automatic classifier has been employed. However, in that paper the authors have verified the proposed methodology on the basis of the set of 500 images with higher quality and where the car colours were clear. In such conditions the efficiency of colour recognition has reached about 90%.

In this study the car make recognition approach has been evaluated using a set of 8,447 images containing 46 various car makes. Training images for pattern matching are taken from the entire data set. In each experiment, an automated procedure for selection of reference patterns per each brand is performed. It involves mutual matching between all pairs of images and selection of the most discriminant patterns in terms of both recognition sensitivity and specificity. First, the influence of two parameters has been investigated: the SIFT matching distance ratio r_d ([0.25,0.95]) and the number of patterns per brand in the reference database N_{ppb} ([3, 10]). In each trial a series of operations has been performed: (1) reference database generation by automated selection of N_{ppb} reliable patterns (if a car make has not got enough samples to supply the reference database plus at least one test sample, it is excluded from the experiment); (2) examination of all remaining test samples by comparing with the reference database; (3) calculation of two efficiency measures, defined as follows:

- recognition efficiency E_{rec} :

$$E_{rec} = \frac{N_{TP}}{N_{TP} + N_{FN}} \cdot 100\% \quad (5)$$

- total efficiency E_{tot} :

$$E_{tot} = \frac{N_{TP}}{N} \cdot 100\% \quad (6)$$

where N is the total number of test samples, N_{TP} and N_{FN} are the numbers of true positive and false negative matches, respectively. $N = N_{TP} + N_{FN} + N_U$, with N_U being the number of unrecognized cases. Figures 9a and 9b show charts of both efficiencies depending on r_d and N_{ppb} .

The lower the r_d value, the more reliable decisions (higher E_{rec}) are obtained and more unclassified cases appear (higher N_U and consequently lower E_{tot}). The highest total efficiency exceeding 70% can be

Table 4 – System efficiency for specific car makes ($r_d=0.80$, $N_{ppb}=7$)

Make	E_{rec} [%]	E_{tot} [%]	N	N_{TP}	N_{FN}	N_U
Seat	84.8	84.8	112	95	17	0
Opel	84.0	83.7	989	828	158	3
Suzuki	82.1	82.1	78	64	14	0
Mercedes	80.0	80.0	631	505	126	0
Ford	76.4	76.1	476	362	112	2
Skoda	74.5	74.2	730	542	186	2
Volvo	72.9	72.9	96	70	26	0
Hyundai	73.0	72.4	127	92	34	1
Chevrolet	72.3	72.3	47	34	13	0
Kia	72.1	72.1	111	80	31	0
Volkswagen	71.3	71.2	1290	918	369	3
Renault	71.4	71.1	768	546	219	3
Dacia	68.6	68.6	35	24	11	0
Honda	64.3	63.8	116	74	41	1
Peugeot	63.8	63.6	379	241	137	1
Audi	60.5	60.5	354	214	140	0
Toyota	59.9	59.9	397	238	159	0
Iveco	59.7	59.7	119	71	48	0
Citroën	55.4	55.1	383	211	170	2
Fiat	54.4	53.5	482	258	216	8
FSO	50.0	50.0	6	3	3	0
Dodge	50.0	50.0	2	1	1	0
Mitsubishi	48.2	46.6	58	27	29	2
BMW	46.2	46.2	119	55	64	0
Mazda	44.9	44.9	69	31	38	0
Chrysler	44.4	42.1	19	8	10	1
Lexus	40.0	40.0	5	2	3	0
Nissan	30.9	30.4	112	34	76	2
Daewoo	28.6	28.6	21	6	15	0
Subaru	20.0	20.0	5	1	4	0
Land Rover	0.0	0.0	5	0	5	0

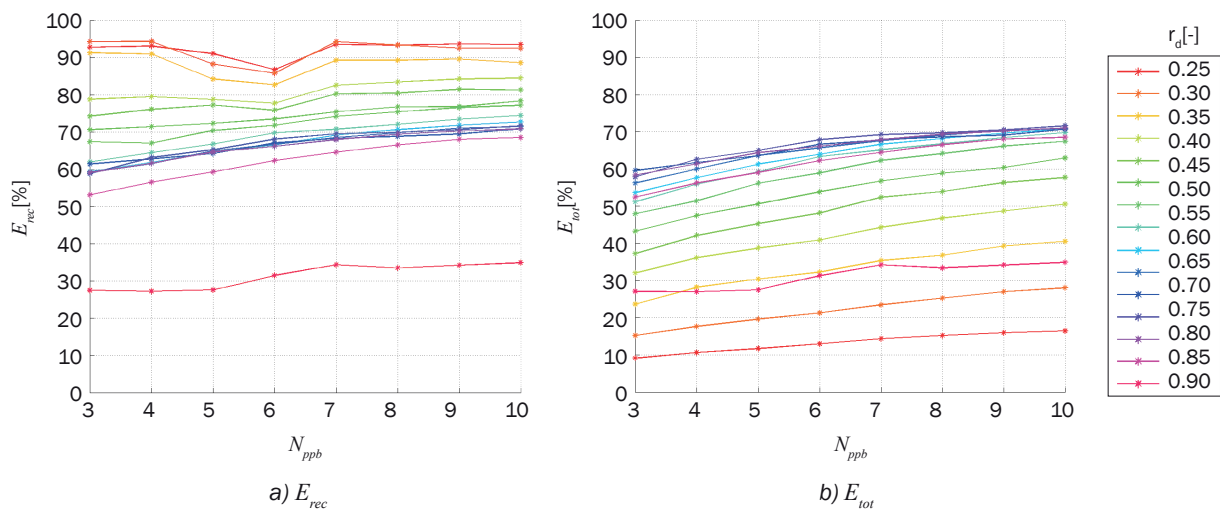


Figure 9 – Car make recognition efficiencies as functions of parameters r_d and N_{ppb}

obtained for $r_d \in [0.65, 0.80]$. On the other hand, E_{tot} shows a growing trend in the domain of the number of patterns per brand.

Finally, *Table 4* presents the efficiency details for all car makes involved in the experiment with $r_d = 0.80$ and $N_{ppb} = 7$. Makes absent due to underrepresentation: Rover, Vauxhall, Lancia, Mini, Smart, Jeep, Infiniti, Tata, Cadillac, Alfa Romeo, Saab, Range Rover, Jaguar, Maserati, Isuzu.

All makes represented in *Table 4* were captured on images. However, these images were not all captured by the camera. About 30% of the total number of car front images were taken in very poor lighting condition and it was not possible to recognize the car brand even by a human.

The main advantages of the presented make recognition system lie (1) in its ability to handle low quality images, (2) in its flexibility in reference database extension and adaptation, and (3) in a large number of testing data. Some earlier studies report high efficiency (96%) of make and model recognition [4] yet the dataset contains pictures of parked cars, taken from small distance (1.5-3 m). The requirement to cover a large number of car models present in real traffic has not been fulfilled in most of the presented approaches: [6] describe the 17-model recognition system with the 91.7% accuracy; [21] show 62.53% accuracy with a database of only 10 car makes and models. The small amount of database samples is given in [32] as the reason of a 45% efficiency, yielded by their car brand recognition algorithm.

5. CONCLUSION

A system for detecting vehicle specific features has been presented. It utilizes real traffic low quality data to recognize the vehicle colour, make and type. Different methods have been proposed for each modality and the obtained results are very promising. In future works the system can be extended to provide more detailed information about the vehicle type i.e. semi-trailer type (box, tank etc.). The ROI detection for colour recognition module will be improved to detect more accurate coloured vehicle elements. Since the vehicle make recognition efficiency exceeds 70% in case of low quality images, the performance improvement might be expected after employing better suited data. It has been also planned to evaluate other pattern matching tools instead of SIFT.

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SYSTEM DETEKЦИИ SZCZEGÓLNYCH CECH POJAZDU NA PODSTAWIE DANYCH NISKIEJ JAKOŚCI

STRESZCZENIE

W artykule przedstawiono system rozpoznawania marki, typu oraz koloru pojazdu na podstawie danych niskiej jakości, pochodzących z urządzeń rejestrujących rzeczywisty ruch drogowy. W celu detekcji szczególnych cech pojazdów zaproponowano trzy metody, które wykorzystują kilka technik z zakresu przetwarzania sygnałów i obrazów, takich jak system wnioskowania rozmytego o strukturze Mamdaniego do rozpoznawania kolorów, czy skalo-niezmiennicze przekształcenie cech (ang. Scale-Invariant Feature Transform) do identyfikacji marki pojazdu. Uzyskane rezultaty są obiecujące, zwłaszcza, że skorzystano z urządzeń dostępnych na stacjach pomiarowych, które nie były dedykowane temu celowi. W przypadku typu pojazdu zaproponowane rozwiązanie charakteryzuje się lepszą dokładnością niż powszechnie wykorzystywane pętle indukcyjne. Wyczerpujące informacje o pojazdach mogą zostać wykorzystane w wielu dziedzinach z zakresu inteligentnych systemów transportowych, w szczególności do nadzoru ruchu drogowego.

SŁOWA KLUCZOWE

detekcja typu pojazdu; detekcja marki pojazdu; detekcja koloru pojazdu; rzeczywiste dane o ruchu drogowym;

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