Fuzzy rules for model based vehicles classification

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Abstract*. The paper presents a method of vehicles shape description using fuzzy rules. This method was intended for automatic class recognition of vehicles recorded in image data. Antecedents of the rules take into account selected shape coefficients determined for reference vehicles images (templates); consequents are associated with classes of vehicles.*

The rules induction procedure requires segments determination of the reference image. Fuzzy rules describe shape and arrangement of these segments that correspond to visible parts of a vehicle. A reference vehicle image for the rules induction is generated on the basis of three-dimensional shape model. A set of rules defined for different shape models enables vehicles classification.

Input data of the fuzzy classifier consists of shape coefficients computed for segments recognised in a registered digital image of vehicle. Segments in the registered images are extracted using background updating, edge detection and area filling algorithms. The devised method is suitable for application in video sensors for road traffic control systems.

Keywords. Vehicles classification, video-detection, fuzzy rules

1 Introduction

Traffic control systems require reliable and real-time traffic information. This information has to be collected by vehicle detectors installed at intersections. The most common detection systems use inductive loops or video sensors. Video-detection becomes more and more popular because it is cost effective and offers a number of advantages such as the ability to classify vehicles and provide complex data on road traffic [9], [11].

Vehicles class recognition is an important task for vision-based sensors. Accomplishment of this task enables advanced traffic control algorithms to be applied. E.g. recognition of public transport vehicles (buses, trams) allows for priority introducing in traffic signals control. Recognition of personal cars, vans, trucks, buses etc. enables determination of optimal assignment of green time for particular crossroad approach. It is obvious that traffic control algorithms using additional information on vehicles classes provides lower delays and higher fluidity level of the traffic in comparison to less sophisticated control strategies.

In this paper a method is introduced that allows for vehicles class recognition on the basis of simple image processing procedure. The recognition algorithm analyses geometrical properties of the image segments determined as foreground regions bounded by edges.

Matching of segments detected in the image with model segments is performed using fuzzy reasoning system. In the reasoning procedure a segments description is taken into consideration that includes several shape parameters. Applied method of image segments description enables considerable reduction of data amount analysed by the reasoning procedure.

The rest of this paper is organized as follows. Section 2 includes a brief survey of vision-based vehicles class recognition methods. A general design of the proposed classification method is presented in section 3. In Section 4 the vehicle models are described. Section 5 introduces the method of image segments extraction. Section 6 includes definitions of segments parameters and merging operation. Section 7 describes induction procedure of fuzzy rules for vehicles classification. In section 8 details of the designed fuzzy reasoning system are discussed. The experiment results are shown in section 9 and finally, conclusions are drawn.

2 Related works

In the field of vision-based vehicles classification numerous methods have been reported so far. All of these methods use various forms of vehicle shape models. Some of the models describe shape of entire vehicle body (3-D models); other models consider selected shape properties or local features arrangement in the vehicle image. Usually operations of vehicle detection and tracking are preliminary steps in the algorithm of vehicles classification.

In [4] a method is introduced that uses vehicle dimensions to classify vehicles into two categories: cars and non-cars (vans, pickup, trucks, buses, etc.). The vehicle length, width, and height are recovered from the 2-D projections of the vehicles, using information about the camera’s location and the fact that in a traffic scene, all motion is along the ground plane. Vehicles models are defined as rectangular image regions with certain dynamic behavior. Correspondences between regions and vehicles are recognized on the basis of tracking results.

A vehicle classification approach that uses parameterised 3-D models is described in [3]. The system uses a 3-D polyhedral model to classify vehicles in a traffic video sequence. The system uses a generic vehicle models based on typical shape. The underlying assumption being that in typical traffic scenes, cars are more common than trucks or other types of vehicles. Using 3-D models partially occluded vehicles can be correctly detected [5]. However, algorithms of this type have higher computational complexity.

Feature-based vehicle detection algorithms [6], [13] include edge detection techniques, corner detection, texture analysis, harr-like features, etc. On the basis of these detection tools the vehicle class recognition methods have been developed [12]. In [8] a vehicles classifier is proposed based on local-feature configuration, which is a generalization of the eigen-window method. It was applied to distinguish four classes: sedan, wagon, mini-van and hatchback. The system requires training images of all target vehicle classes. These training images are created using a 3-dimentional computer graphic tool.

Another approach combines elements of 3-D models with feature-based methods. Local 3D curve-groups (probes) are used, which when projected into video frames are features for recognizing vehicle classes in video sequence [2]. The recognition procedure is based on class probability densities for groups of 3-D distances between pairs of 3-D probes. It is implemented by having a class probability distribution for groups of distances between pairs of 3-D probes for each vehicle class. This classifier was applied to three classes of vehicles: sedans, minivans and SUV’s.

The method introduced in this paper uses fuzzy rules [1] to describe shape of a vehicle model. Proposed rules allow for level evaluation of similarity between image objects and assumed vehicle model. On this base the reasoning procedure is performed for vehicles class recognition. Main advantage of this method is complexity reduction of the classification algorithm due to processing of simplified image description.

3 Proposed method

The aim of the presented image analysis algorithm is to recognise class of a vehicle recorded in an input image. For vehicles class recognition fuzzy classification rules have been applied. These rules define reasoning procedure which is based on description matching of the reference image with objects extracted from input image. Scheme of the introduced algorithm is presented in fig. 1.

Proposed method of image segments description takes into account shape coefficients and mutual location of these segments. The description method was applied for both segments of 2-D model (reference image) as well as segments extracted from input image.

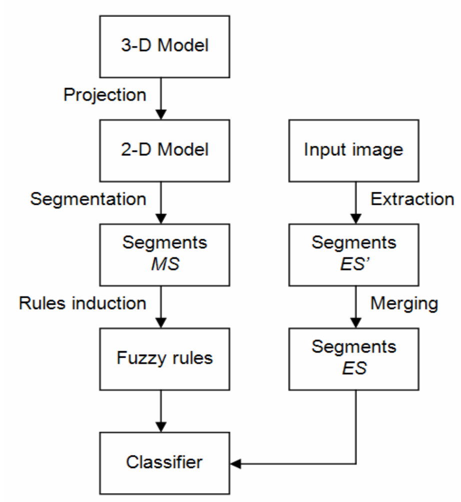


Figure 1. Scheme of the vehicles classification algorithm

Segments *ES′* are determined in the input image on the basis of edges detection and background extraction results. They correspond to regions of input image that are bounded by edges and do not belong to the background.

Preparatory processing of the extraction results includes segments merging of *ES′* into segments *ES*, that match better with shape of the model segments MS. The need for segments merging is connected with assumed fidelity level of the model, which does not take into account minor parts of vehicle like headlights or number plate.

The 3-D model [10] describes faces arrangement of a vehicle body. This model is transformed into 2-D model, for defined locations of the vehicle and camera. Thus, the 2-D model establishes a reference vehicle image of a given class that is located in a specific place within the scene. Faces of the 3-D model, projected on image plane, defines segments *MS* of the 2-D model.

Fuzzy classification rules are inducted on the basis of segments determined for vehicle model. Antecedents of the rules take into account parameters included in the description of segments *MS*; consequents indicate class of the vehicle. Rules induction process consists in fuzzyfication of the parameters describing segments *MS* of the model.

The procedures of segments merging, rules induction and classification are performed using devised representation method of image segments (segments description based on selected geometric parameters). These procedures are not executed directly on image data, what is crucial in reducing computational complexity of the classification algorithm.

4 Vehicle models processing

The vehicle model has to be defined for each vehicles class that is taken into consideration by the recognition procedure. The example of vehicle model for sedan class is presented in fig. 2.

Definition of the 3-D vehicle model comprises its width w (dimension along x" axis) and coordinates of eight vertices that describe the shape of the model on plane y"-z". This model can be written in form of a 8 x 2 matrix: $M = [m_{ij}]$, where (m_{i0}, m_{i1}) are coordinates of i-th vertex, $i = 1\ldots 8$.

The 2-D model (reference image) is generated for a given vehicle position in the scene and rotation angle ϕ. Position is defined by vector $L = [l_1, 0, l_2]^T$ that also determines the origin of the vehicle-fixed system in the road plane.

3-D vehicle model (fig. 2) is created in road-fixed coordinate system on the basis of matrix M. The vehicle model is rotated around y" axis and translated by the position vector.

The next operation in the template generation algorithm is the calculation of viewing transformation [7], which consist of: conversion of road-fixed system to camera coordinate system, visibility calculations and transformation for perspective projection. As a result of this operation coordinates of pixels are obtained that correspond to visible vertices of the vehicle model.

The 2-D vehicle model comprises pairs of vertices that are linked by edges. Edges in the reference image are generated linking pixels representing vertices of the model, which were determined in the previous operation. Bersenham's line drawing algorithm has been applied for selection of edge pixels.

After edges drawing, modified Smith's flood fill algorithm is used to mark pixels in particular segments (*MS*) bounded by edges. These segments of reference image correspond to faces of the 3-D vehicle model. At the same time geometrical parameters of the segments are computed. As a result of this operation a complete description of the model segments *MS* is obtained.

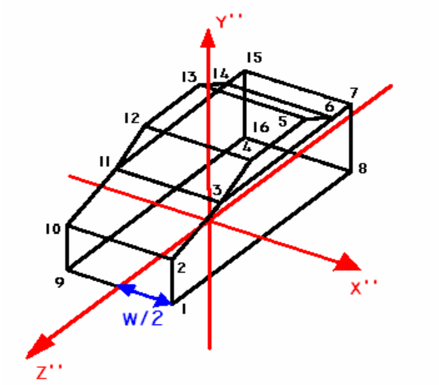


Figure 2. Vehicle model

5 Image segments extraction

Segments *ES'* in the 8-bit gray-scale input images are extracted using background updating, edge detection and area filling algorithms. The crucial task of this operation is to extract segments that correspond with visible parts of vehicles recorded in the image.

The proposed background recognition algorithm [10] for sequence of input images includes short-term and long-term updating procedures that enable to cope with illumination changes and shadows of stationary objects.

Background estimation procedure uses a number of tables containing information on the frequency of pixel values. It was experimentally verified that dividing the range of pixel values into 3 partitions is sufficient to prepare a useful statistical model of pixel values. Background update procedures assign the most probable mean values of pixels to background pixels using a linear function of previous background value and current pixel value.

Edges are detected in input image as well as in background. In the discussed algorithm a grey-scale morphological operator is used for edges detection. Pre-processing includes median filtering. After median filtering, erosion and dilatation are executed in parallel. In the next step subtraction is performed for images obtained as results of erosion and dilatation.

Pixels values obtained after morphological transformations (edge image) are binarized. On the basis of two binary edge images (one for frame and one for background) objects map is computed: $O_m(x,y) \in \{0,1,2\}$. Value 2 in the map O_m indicates edge elements of vehicles (that are detected in the frame, but are not detected in the background); value 1 distinguishes elements of vehicles that do not belong to the background, value 0 denotes regions, where background is visible (no foreground object is present).

Finally, just like in model segmentation, the flood fill algorithm is used to determine input image segments (*ES*) as well as geometrical parameters for their description.

The algorithm for vehicles extraction was tested using a number of image sequences of traffic scenes taken in different lighting conditions and using various cameras. Results show that it ensures satisfactory accuracy and sufficient speed of processing.

6 Segments description and merging

Introduced shape description method for objects registered in an image is based on selected geometrical parameters of the image segments. The description method applied for segments of reference image (model) as well as for extracted segments of the input image remains the same.

Description of *i*-th image segment is defined by the formula:

$$S_i = \left(A_i, x_i, y_i, x_i^{\min}, x_i^{\max}, y_i^{\min}, y_i^{\max}\right), \tag{1}$$

where:

A_i - area of the segment,

$c_i = \left(x_i, y_i\right)$ - centre of mass determined for the segment,

$w(S_i) = x_i^{\max} - x_i^{\min}$ - width of the segment,

$h(S_i) = y_i^{\max} - y_i^{\min}$ - height of the segment,

$q(S_i) = \dfrac{w(S_i) \cdot h(S_i)}{A_i}$ - shape coefficient.

Computations of the segments parameters, defined above, are performed for coordination system *x-y* (fig. 3) that has orientation determined by the model orientation in camera coordinate system.

The principles of segments merging operation are illustrated in fig. 3. Parameters of merged segments are depicted in fig. 3 a); fig. 3b) presents results of the segments merging.

Formally, the merging operation is denoted by relation:

$$S_k = S_i \,{}^{\mathrm{M}}\, S_j, \tag{2}$$

which means that segment S_k is created by merging S_i with S_j and parameters of its description are computed according to the following formulas:

$$\begin{aligned}
A_k &= A_i + A_j, \\
x_k &= \frac{A_i x_i + A_j x_j}{A_i + A_j}, \\
y_k &= \frac{A_i y_i + A_j y_j}{A_i + A_j}, \\
x_k^{\min} &= \min\left(x_i^{\min}, x_j^{\min}\right), \\
y_k^{\min} &= \min\left(y_i^{\min}, y_j^{\min}\right), \\
x_k^{\max} &= \max\left(x_i^{\max}, x_j^{\max}\right), \\
y_k^{\max} &= \max\left(y_i^{\max}, y_j^{\max}\right).
\end{aligned} \tag{3}$$

a)

b)

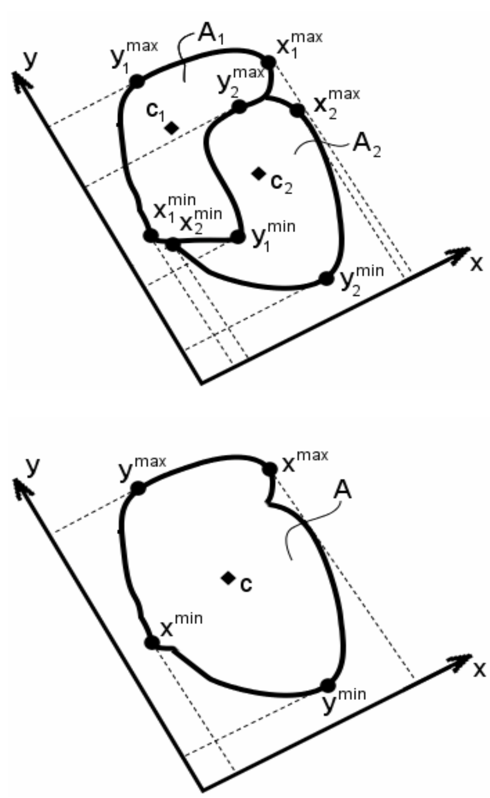


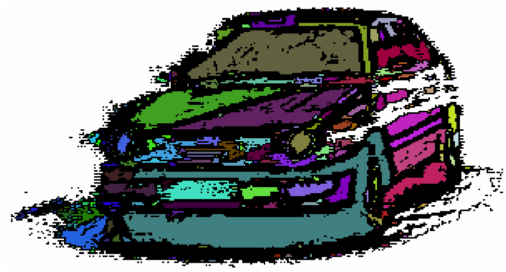
Figure 3. Segments description and merging operation

The merging operation has following properties that are important for its implementation:

$$\begin{aligned}
&S_i \,{}^{\mathrm{M}}\, S_j = S_j \,{}^{\mathrm{M}}\, S_i, \\
&S_i \,{}^{\mathrm{M}}\left(S_j \,{}^{\mathrm{M}}\, S_k\right) = \left(S_j \,{}^{\mathrm{M}}\, S_i\right) {}^{\mathrm{M}}\, S_k.
\end{aligned} \tag{4}$$

Application example of the segments merging operation for a vehicle image is depicted in fig. 4. All segments are marked with different colours. Fig. 4 a) presents segments *ES'* extracted from the input image and fig 4 b) shows segments *ES* obtained as a result of the merging operation. This operation takes into account vehicle model that is also drawn in fig. 4 b). The extracted segments *ES′* are merged together if their mass centres lie inside one segment of the *MS* model. In this way the best possible matching is achieved for segments of the input image and the model. Such preparatory processing is necessary for correct vehicle class recognizing by fuzzy rules that are introduced in the following section.

a)



b)

Figure 4. Segments: a) extracted from original image, b) obtained after merging operation

7 Rules induction

Classification rules are produced on the basis of reference images (models) and an input image. Set *MS* includes descriptions of all segments determined for 2-D vehicle model of class *c*:

$$MS^c = \{S_j^c\},\ j = 1 \ldots n(c)\,. \tag{5}$$

Segments extracted from input image are described by elements of set *ES*:

$$ES = \{S_i\},\ i = 1 \ldots m\,. \tag{6}$$

For every vehicles class a set of classification rules is created including three types of rules, connected with different aspects of the segments layout: shape rules, placement rules and arrangement rules.

Rules (R1) describe shape of segments for the vehicle model of class *c* using shape coefficients. They allow for similarity determination of segments from *MS* and *ES*.

$$\textbf{if } A_i \text{ is } \tilde{A}_j^c \textbf{ and } q(S_i) \text{ is } \tilde{q}(S_j^c) \textbf{ then } p(S_i) \text{ is } j\,, \tag{R1}$$

where:
$i = 1 \ldots m,\ j = 1 \ldots n(c)$.

Rules (R2) describe mutual placement of the segments. Using these rules each pair of segments from *ES* is processed. It is performed by comparing the relative location of their mass centres (defined by [*dx*, *dy*] vector) with the mass centres arrangement of the model segments (j_1, j_2).

$$\begin{aligned}&\textbf{if } dx(S_{i_1}, S_{i_2}) \text{ is } \tilde{d}x(S_{j_1}^c, S_{j_2}^c) \textbf{ and}\\ &dy(S_{i_1}, S_{i_2}) \text{ is } \tilde{d}y(S_{j_1}^c, S_{j_2}^c) \textbf{ and } p(S_{i_2}) \text{ is } j_2\,,\\ &\textbf{then } d(S_{i_1}, S_{j_2}^c) \text{ is } (j_1, j_2)\end{aligned} \tag{R2}$$

where:
$i_1 = 1 \ldots m,\ i_2 = 1 \ldots m,\ i_1 \neq i_2$,
$j_1 = 1,\ j_2 = 2 \ldots n(c)$,
$dx(S_i, S_j) = x_i - x_j$,
$dy(S_i, S_j) = y_i - y_j$.

The spatial arrangement rules (R3) take into account placement of all model segments. Both the segments shape similarity and segments locations are checked. It is performed using results of the previous reasoning stages that exploit (R1) and (R2) rules.

$$\begin{aligned}&\textbf{if } p(S_i) \text{ is } 1 \textbf{ and } d(S_i, S_2^c) \text{ is } (1,2) \textbf{ and}\\ &d(S_i, S_3^c) \text{ is } (1,3) \textbf{ and} \ldots \textbf{and } d(S_i, S_{n(c)}^c)\\ &\text{is } (1, n(c)) \textbf{ then } class \text{ is } c\,,\end{aligned} \tag{R3}$$

where:
$i = 1 \ldots m$.

The „~” symbol was used in rules definitions (R1) and (R2) to indicate fuzzy sets having trapezoidal membership functions. The membership functions are determined for specific values of segment description parameters. E.g.: the fuzzy set $\tilde{A}_j^c$ is determined for the crisp area value A_j^c of segment *j* in the reference image. The membership function of $\tilde{A}_j^c$ is given by formula:

$$\mu_{\tilde{A}_j^c}(x)=\begin{cases}0 & \text{for } x\le a,\\ \frac{x-a}{b-a} & \text{for } a<x\le b,\\ 1 & \text{for } b<x<c,\ .\\ \frac{d-x}{d-c} & \text{for } c<x\le d,\\ 0 & \text{for } x>d.\end{cases} \tag{7}$$

Fig. 5 illustrates an example of rules induction procedure for input image that comprises three segments (m = 3) and reference image (2-D vehicle model) composed of two segments ($n(c)$ = 2). The edges of model segments are marked with dashed line.

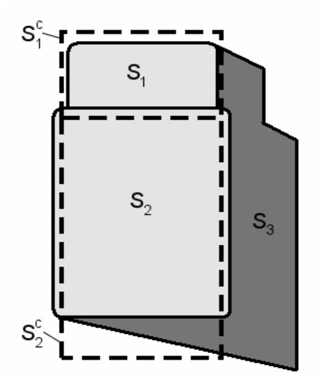


Figure 5. Segments example of model (S_1^c, S_2^c)) and input image ($S_1 - S_3$)

For the assumed images the shape rules are created determining similarity of segments:

$\textbf{if } A_1 \text{ is } \tilde{A}_1^c \textbf{ and } q(S_1) \text{ is } \tilde{q}(S_1^c) \textbf{ then } p(S_1) \text{ is } 1$
$\textbf{if } A_1 \text{ is } \tilde{A}_2^c \textbf{ and } q(S_1) \text{ is } \tilde{q}(S_2^c) \textbf{ then } p(S_1) \text{ is } 2$
$\textbf{if } A_2 \text{ is } \tilde{A}_1^c \textbf{ and } q(S_2) \text{ is } \tilde{q}(S_1^c) \textbf{ then } p(S_2) \text{ is } 1$
$\textbf{if } A_2 \text{ is } \tilde{A}_2^c \textbf{ and } q(S_2) \text{ is } \tilde{q}(S_2^c) \textbf{ then } p(S_2) \text{ is } 2$
$\textbf{if } A_3 \text{ is } \tilde{A}_1^c \textbf{ and } q(S_3) \text{ is } \tilde{q}(S_1^c) \textbf{ then } p(S_3) \text{ is } 1$
$\textbf{if } A_3 \text{ is } \tilde{A}_2^c \textbf{ and } q(S_3) \text{ is } \tilde{q}(S_2^c) \textbf{ then } p(S_3) \text{ is } 2$

In next step the placement rules induction is performed. A result of this operation is the following set of rules:

$\textbf{if } dx(S_1,S_2) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_1,S_2) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_2) \text{ is } 2 \textbf{ then } d(S_1,S_2^c) \text{ is } (1,2)$
$\textbf{if } dx(S_1,S_3) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_1,S_3) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_3) \text{ is } 2 \textbf{ then } d(S_1,S_2^c) \text{ is } (1,2)$
$\textbf{if } dx(S_2,S_1) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_2,S_1) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_1) \text{ is } 2 \textbf{ then } d(S_2,S_2^c) \text{ is } (1,2)$
$\textbf{if } dx(S_2,S_3) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_2,S_3) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_3) \text{ is } 2 \textbf{ then } d(S_2,S_2^c) \text{ is } (1,2)$
$\textbf{if } dx(S_3,S_1) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_3,S_1) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_1) \text{ is } 2 \textbf{ then } d(S_3,S_2^c) \text{ is } (1,2)$
$\textbf{if } dx(S_3,S_2) \text{ is } \tilde{dx}(S_1^c,S_2^c) \textbf{ and } dy(S_3,S_2) \text{ is } \tilde{dy}(S_1^c,S_2^c) \textbf{ and } p(S_2) \text{ is } 2 \textbf{ then } d(S_3,S_2^c) \text{ is } (1,2)$

Finally, the arrangement rules (R3) are produced for assumed vehicles class. These rules allow for membership degree determination in class c of the recorded vehicle.

$\textbf{if } p(S_1) \text{ is } 1 \textbf{ and } d(S_1,S_2^c) \text{ is } (1,2) \textbf{ then } \mathit{class} \text{ is } c$
$\textbf{if } p(S_2) \text{ is } 1 \textbf{ and } d(S_2,S_2^c) \text{ is } (1,2) \textbf{ then } \mathit{class} \text{ is } c$
$\textbf{if } p(S_3) \text{ is } 1 \textbf{ and } d(S_3,S_2^c) \text{ is } (1,2) \textbf{ then } \mathit{class} \text{ is } c$

8 Vehicles class recognition

Class of a registered vehicle is recognised using fuzzy reasoning system with base of rules that are defined in the previous section. Input data of the reasoning system is fuzzified into type-0 fuzzy sets (singleton fuzzification). The system uses minimum t-norm and Mamdani reasoning method [1].

Due to above assumptions, the membership functions for consequents of rules (R1) - (R3) are computed according to the formulas (8) - (10). In the first stage of the reasoning procedure a membership function is computed for each segment S_i that determines its similarity to particular segments S_j^c of the model.

$$\mu_{p(S_i)}(j)=\min\left[\mu_{\tilde{A}_j^c}(A_i),\mu_{\tilde{q}(S_j^c)}(q(S_i))\right] , \tag{8}$$
$$i=1...m,\ j=1...n(c) .$$

In the second stage another membership function is evaluated to check if the segments arrangement in the model is consistent with the model definition:

$$\begin{aligned}\mu_{d(S_i,S_{j2}^c)}(j_1,j_2)=&\\ =\max_{i_2}&\left\{\min\left[\mu_{\tilde{dx}(S_{j1}^c,S_{j2}^c)}(dx(S_{i_1},S_{i_2})),\right.\right.\\ &\left.\left.\mu_{\tilde{dy}(S_{j1}^c,S_{j2}^c)}(dy(S_{i_1},S_{i_2})),\mu_{p(S_{i_2})}(j_2)\right]\right\},\end{aligned} \tag{9}$$
$$i_1=1...m,\ i_2=1...m,\ i_1\ne i_2 ,$$

$j_1 = 1, j_2 = 2 \ldots n(c)$.

At last, the third membership function determines similarity level of the object recorded in input image and vehicle shape model of class c:

$$\mu_{class}(c) = \max_i \left\{ \min \left\{ \mu_{p(S_i)}(1), \min_j \left[\mu_{d(S_i, S_j^c)}(1, j) \right] \right\} \right\}, \quad i = 1 \ldots m. \tag{10}$$

The number of recognised vehicle class is a product of the defuzzification process. The defuzzification procedure is determined by the maximal membership function method:

$$\overline{class} = \arg \max_c \mu_{class}(c). \tag{11}$$

9. Experimental results

Experiments were carried out with video data of a traffic lane. The tests were performed using images selected in sequences of traffic scenes, where vehicles of different classes have been recorded. Examples of the test images are presented in fig. 6.

Figure 6. Test images

Vehicles shape models used in this experiment are depicted in fig. 7. They correspond to the following classes of vehicles: (a) personal car, (b) van (c) truck, (d) bus, (e) tractor-trailer. Using introduced fuzzy rules the segments determined for vehicles models were matched with those extracted from input images. The devised reasoning procedure was implemented for vehicle class recognition.

Table 1 shows results of the experiment for selected examples (fig. 6). Maximal values of the membership function $\mu_{class}(c)$ for each input image (row) are marked with grey. These maximal values indicate the recognised class that is related to particular model (column).

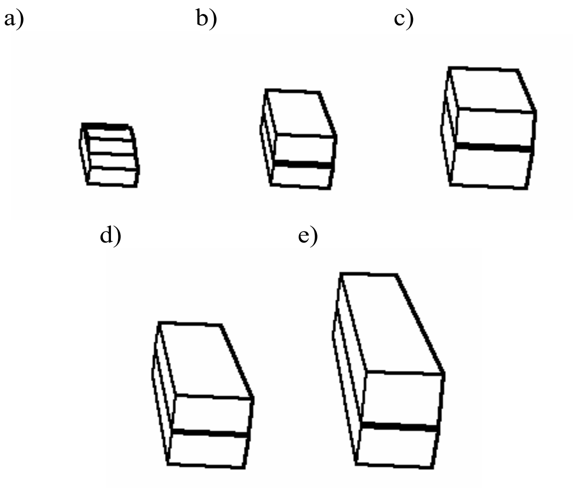


Figure 7. Vehicle models used in the experiment

Preliminary tests, reported in this section, shows that for most cases the proposed vehicle recognition system provides correct results. The results strongly depend on correctness of the segments extraction in input images.

Table 1. Values of the membership function $\mu_{class}(c)$

Model / Image	a	b	c	d	e
a	0,43	0,28	0,13	0,13	0,00
b	0,13	0,37	0,31	0,07	0,00
c	0,42	0,41	0,64	0,00	0,00
d	0,00	0,00	0,00	0,00	0,46
e	0,00	0,27	0,00	0,00	0,40

10 Conclusion

The paper presents a method of vehicles shape description using fuzzy rules. This method was implemented for automatic classification of vehicles recorded in image data. For every vehicles class a set of classification rules is created. A fuzzy reasoning system uses these rules for class recognition.

Preliminary outdoor tests confirmed that the proposed fuzzy model-based method is effective to vehicle class recognition. It was demonstrated that the system can categorize vehicles into five classes. In future work, this system will be tested for more vehicle classes. Larger video database of vehicles will be created for further experiments to enhance the proposed method.

It should be noticed that the low computational complexity makes the presented method suitable for implementation in road traffic control systems.

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