Selected aspects of digital image processing applications in ITS

P. MRÓWKA[a], M. OLEJNICZAK[a]
[a] NEUROSOFT SP. Z O. O., Robotnicza 72, 53-608 Wrocław, Poland
EMAIL: pawel.mrowka@neurosoft.pl

ABSTRACT

Digital image processing algorithms are commonly applied in Intelligent Transport Systems (ITS). Their effective operation is conditioned on the high robustness to real-life image distortions and the computational complexity suitable for implementation on a non expensive industrial computer. The paper presents three original image analysis methods designed for the ITS, with special attention paid on aforementioned conditions. Colour image parametrization method for the traffic light state classifier was described. The algorithm utilizes CIELAB colour space properties. The method of vehicle edges parametrization for the make and model classifier was presented. The proposed representation relies on thresholded coefficients of gradient magnitude approximation in low dimensional space. The paper presents also the method of image characteristic features detection for the licence plates localization task. The detection is performed by means of appropriately designed filters with low computational complexity.

KEYWORDS: digital image processing, image parametrization, traffic light classification, colour recognition, make and model recognition

1. Introduction

In recent years rapidly growing popularity of video-based surveillance systems can be observed. The reasons behind this growth are i.a.: fall of the digital video equipment prices, rise of computational power of the video processing hardware, development of efficient image processing algorithms dedicated to objects recognition, tracking and behaviour analysis.

Modern Intelligent Transport Systems (ITS) utilize several image processing subsystems: automatic number plate recognition (ANPR), vehicle make and model recognition (MMR), vehicle and pedestrian detection, tracking and behaviour analysis, traffic congestion and flow analysis, red light violation enforcement, speed-from-video measurement, automatic emergency detection etc.

The main advantages of video-based systems are: relatively low price, installation non-invasive to pavement, high mobility. However, video analysis algorithms effectiveness can be severely decreased due to inappropriate lighting conditions and image distortions caused by many reasons such as shadows, overexposures, motion blur, precipitation etc.

Real-life application requires the algorithms to be robust to image distortions and their computational complexity allow implementation on a non expensive industrial computer. The paper presents three original image analysis methods designed as the parts of Neurocar ITS system.

2. Colour parametrization for traffic light state classifier

2.1 Role of parametrization

The red light violation enforcement system utilizes a video based traffic light signal classification module. The module consists of three main parts: traffic light position detector, colour image features extractor and state classifier. The detector continuously tracks the light position, changing due to wind, vibrations, thermal expansion of mounting poles etc. Knowing the position, features describing light state can be calculated and then fed to the state classifier. The classifier is designed as a binary non-linear maximum margin classifier, similar to the SVM. Activity of each

light field (red, yellow, green) is separately classified and then overall signal (off, red, red-yellow, green, yellow) is computed.

The feature extraction (parametrization) method should be computationally plausible for 25 fps real time operation and provide robustness to the wide spectrum of lighting conditions variation and image distortions.

2.2 Feature extraction

A rectangular reception field r is defined and automatically located for each light field (Fig. 1.). Due to large variation (Fig. 2.), there is no shape analysis applied. The reception field output is the simple average of its pixels values. A colour space used to pixel representation plays crucial role in classification [1, 2, 3]. A few spaces was tested during the experiments. The details of RGB (image source native) and CIELAB (perceptual motivated) [4] spaces usage are described below.

For each reception field r calculate the pixel values averages:
- RGB colour space: S_R^r, S_G^r, S_B^r
- CIELAB color space: S_L^r, S_a^r, S_b^r

For RGB space calculate also:

$$S_I^r = 0.30\,S_R^r + 0.59\,S_G^r + 0.11\,S_B^r \qquad (1)$$

$$S_C^r = S_R^r - S_B^r \qquad (2)$$

where S_I^r is RGB luminance and S_C^r is an approximation of opponent colour space direction [4].

Our proposed traffic light descriptor feature vector $\mathbf{v}^r$ is constructed in the following way:
- RGB colour space

$$\mathbf{v}^r = [S_R^r, S_G^r, S_B^r, \max_i(S_I^i), \min_i(S_I^i), \max_i(S_C^i), \min_i(S_C^i)]^T \qquad (3)$$

- b) CIELAB color space

$$\mathbf{v}^r = [S_L^r, S_a^r, S_b^r, \max_i(S_L^i), \min_i(S_L^i), \max_i(S_a^i), \min_i(S_a^i)]^T \qquad (4)$$

Both S_C^r and S_a^r values extrema are introduced due to their high discriminative properties with respect to greenish - reddish colours. Luminance values S_I^r and S_L^r extrema are added to provide information off overall lightness range within all reception fields. Index i goes through all reception field in the signaller.

Fig. 1. Reception fields (rectangles) over the traffic light

2.3 Results

Training sample set contained 4419 examples while the test set contained 20584 examples. Examples represented different locations, lighting and weather conditions. All system parameters except used colour space were constant. Table 1. presents obtained classification results from training and test.

Table 1. Results of traffic light state classification

Colour space	Classification results in samples set	
	Training	Test (with 95% confidence interval)
RGB	99.743%	99.835% +/- 0.055%
CIELAB	100.000%	99.898% +/- 0.044%

Some examples of incorrect classification are shown on Fig. 3. Results show that designed traffic light parametrization together with the classifier provide satisfactory classification performance and generalization. The results show that introducing appropriate non-linear colour space transformation causes significant classification performance improvement. This is due to better separation of different classes samples in the feature space.

Fig. 2. Examples of various environmental conditions classifier has to cope with

Fig. 3. Examples of incorrect traffic light state classification (CIELAB colour space): top-left: classified as green, top-right: classified as yellow, bottom-left: classified as red-yellow, bottom-right: classified as green

3. Vehicle front image edges parametrization for MMR

3.1 Vehicle front image based MMR

Video-based make and model recognition can rely on different views of vehicle. Distant view [5, 6], rear view [7] or front view [8] approaches are known. The developed make and model recognition system uses the image of the vehicle's front, where region of interest (RoI) is located in the vicinity of the license plate. This region contains the most of discriminative features like headlights contours, grille, bumper, logo. Usually these features have also highly visible contours (edges).

The principle of our system operation is based on the matching of the descriptor of vehicle being recognized with the reference database. The base contains descriptors of few thousands vehicle examples, covering over 2000 distinct models. Because of the size of the base, descriptor have to be short enough to ensure the matching process time and memory consumption to be acceptable (a few dozens of milliseconds, a few hundreds of MB). The designed vehicle descriptor has length equal 1758 bytes.

Before the parametrization takes place, following steps have to be taken:
1. licence plate position detection,
2. RoI extraction with geometrical normalization, where RoI position is related to licence plate position and geometrical normalization is related to scene (camera) parameters,
3. RoI contrast normalization.

Fig. 4. shows RoI example after aforementioned steps. Subsequently, rectangular tiles are extracted and undergo edges parametrization. The vehicle descriptor is built of concatenated parameters from all used tiles. Most of system's parameters values (e.g. RoI location and size, tiles number, locations and sizes) were determined via optimization during the system training phase.
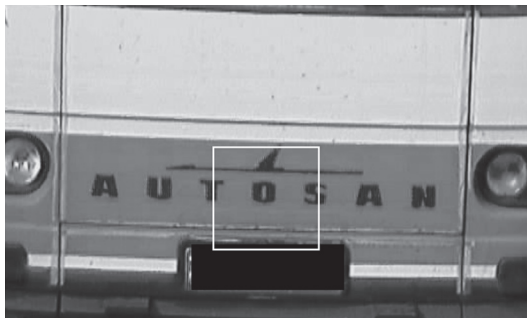

Fig. 4. Example of the region of interest (RoI) of a vehicle. Selected tile example marked by the rectangle

3.2 Edges parametrization

The tile edges parametrization has to provide high robustness to image distortions and random differences between vehicles belonging to the same class. Computational cost of parametrization has also to be plausible for real-time operation.

Following tile parametrization steps was proposed:
1. S - grayscale image, with vectorized representation **s**
2. G - gradient magnitude of S, with vectorized representation **g**
3. **a** - coefficients of approximation of **g** in the orthonormal base, which basis vectors constitute rows of matrix **P**

$$a = P g \qquad (5)$$

3. **b** - coefficients after sigmoid non-linearity applied element-wise to **a**

$$b_i = \tanh(\alpha_i (a_i - \beta_i)) \qquad (6)$$

Values of P, α_i, β_i were determined in the course of optimization during the system training, where classification error was used as the minimized objective function.

Examples of parametrization stages outputs for selected tile (marked on Fig. 4.) are shown on Fig. 5.
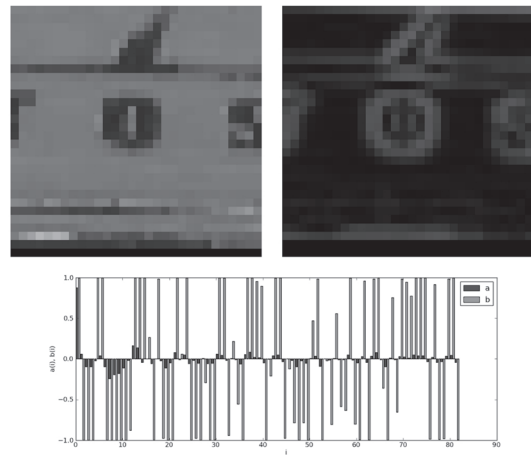

Fig. 5. Example of selected tile (rectangle on Fig. 4.) parametrization outputs. top-left: S, top-right: G, bottom: **a, b**

3.3 Results

The tile marked in Fig 3.1. was selected as the example for subsequent calculations. In the case of selected tile, parametrization vectors have following lengths: $\dim(\mathbf{s}) = \dim(\mathbf{g}) = 900$, $\dim(\mathbf{a}) = \dim(\mathbf{b}) = 82$.

In order to compare discriminative properties of each parametrization steps outputs, following discrimination measure was proposed:

$$d_i = \frac{\min_{j \in C_i^c}(\|x_i - x_j\|)}{\min_{j \in C_i, j \neq i}(\|x_i - x_j\|)} \qquad (7)$$

where $\mathbf{x}_i$ stands for descriptor of i-th sample, C_i stands for the set of sample indices sharing the same class with i-th sample, C_i^c stands for the complement of C_i. Euclidean norm was used.

The test set contained 3618 vehicles divided into 159 vehicle model classes. Table 3.1. presents quartiles of discrimination measure d distribution over the test samples, where **s, g, a, b** were substituted in the place of **x** in eq. 7, respectively. Additionally, percentile for $d = 1.0$ (decision boundary) was given.

Table 3.1 Quartiles of *d* measure distribution over the test set for different parametrizations

Quartiles of d measure distribution	Parametrization step			
	s dim(s) = 900	g dim(g) = 900	a dim(a) = 82	b dim(b) = 82
Q1	0.816	0.846	0.813	0.930
Q2	0.952	0.980	1.028	1.059
Q3	1.158	1.200	1.375	1.254
percentile for d = 1.0	57.74	53.317	47.12	39.44

The obtained results show that subsequent stages of proposed edges parametrization ensure discrimination capability increase together with significant descriptor length reduction. Complete classifier utilizing descriptor of length 1758 reaches real-life performance at level of 97% correctly classified vehicle manufacturers.

4. Low complexity features detection for licence plate finding

License plate position detection is the one of the most challenging among image processing task utilized in ITS. This is due to the fact, that the plate is a relatively small object embedded in highly cluttered environment. Furthermore, nowadays processed images have often HD resolution, where number of processed pixels exceeds 2 million.

A following low complexity feature detection algorithm was proposed to deal with aforementioned issues.

```
INPUT:  I - MxN 8-bit grayscale image
        t1, t2, t3 - thresholds
OUTPUT: O - MxN binary image

J := MxN auxiliary table initialized with
zeros
FOR y IN 0..N-1:
  FOR x IN 0..M-3:
    D(x) := I(x+2,y) - I(x,y)
  FOR x IN 3..M-3:
    IF D(x-2)<-t1 AND (D(x)>t1 OR D(x+1)>t1
OR D(x+2)>t1):
      J(x,y) := abs(D(x-2))
    IF D(x-2)>t2 AND (D(x)<-t2 OR D(x+1)<-t2
OR D(x+2)<-t2):
      J(x-3,y) := max(O(x-3,y), abs(D(x-2)))
FOR EACH (x,y):
  O(x,y) := J(x,y) > t3 ? 1 : 0
```

The developed algorithm ensures significant reduction in source image information, necessary to real-time operation of subsequent detector stages (i.a. graph based features clustering), while plate characteristic marks are still well preserved.

In the example shown on Fig. 6. input image information entropy (assuming pixel spatial independence) equals 6.66 bit/pixel, while output binary image entropy equals 0.25 bit/pixel.

Fig. 6. Input (left) and output (right) of feature extraction method for the plate detector

5. Conclusion

The paper presented three original image processing algorithms used in real-time, highly efficient and market-available video analysis ITS subsystems. In all of them, application of suitable non-linear functions at early stage of image processing allowed achievement of satisfactory robustness to distortions and random variations, while keeping computational cost low enough to make implementation on plain, small industrial computer possible.

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