Automatic Real-time Vehicle Classification by Image Colour Component Based Template Matching

Ahmet Orun*
De Montfort University, Faculty of Computing, Engineering and media,
Leicester UK Email: aorun@dmu.ac.uk. Phone: +44(0)116 3664408

Abstract

Selection of appropriate template matching algorithms to run effectively on real-time low-cost systems is always major issue. This is due to unpredictable changes in image scene which often necessitate more sophisticated real-time algorithms to retain image consistency. Inefficiency of low cost auxiliary hardware and time limitations are the major constraints in using these sorts of algorithms. The real-time system introduced here copes with these problems utilising a fast running template matching algorithm, which makes use of best colour band selection. The system uses fast running real-time algorithms to achieve template matching and vehicle classification at about 4 frames/sec on low-cost hardware. The colour image sequences have been taken by a fixed CCTV camera overlooking a busy multi-lane road.

Keywords: Vehicle classification, template matching, CCTV, colour image

1. Introduction

Template matching is a simple method for achieving the fast classification of vehicles in image sequences taken by a CCTV camera. A description of template matching and the underlying theory can be found in Ballard and Brown (1982) or Davies (1997). The advantage of template matching over other more elaborate methods for vehicle classification is that it can be applied in real-time using only low cost hardware. Many authors describe methods for segmenting vehicles in image sequences. Rittscher et al. (2000) describe a Markov random field model for pixel grey levels. The model is used to find pixels which have a high probability of being contained within a vehicle. Beymer et al. (1997) group feature points to locate the image of a vehicle. Koller et al. (1994) initialise a vehicle tracking algorithm by detecting regions in which the current image in a sequence differs from the background image. They fit a spline contour about each region and track using two Kalman filters, one for the motion of the vehicle and the other for the control points of the spline contour. Cucchiara et al. (1999) implement a vehicle detection and tracking system on low cost hardware, namely SRAM based Field Programmable Gate Arrays. A moving vehicle is detected by frame image differencing. This yields a 'blob' approximating to the apparent shape of the vehicle. The apparent shape is recovered more accurately by adjusting the blob such that its boundaries coincide with image regions with high grey level gradients. Rajagopalan et al. (1999) detect vehicles by modelling the higher order moments of the grey level values within vehicle outlines. In contrast with the many papers on segmenting images of vehicles, there are far fewer papers on vehicle classification. Sullivan (1992) uses wire frame models to locate and classify vehicles in single image. Lim et al. (1995) present a vehicle classification system for electronic road pricing. There are many other general methods for object classification, for example methods based on simple properties of regions segmented out of the image. These properties include area, perimeter, semi-major axis, semi-minor axis (Kitchen and Pugh 1983). Such methods are not useful in this application because the blobs corresponding to vehicles are poorly structured, for example as shown in Figure 1. However none of the above papers deal with the use of colour to improve classification results.

The main contributions of this paper are two related techniques; one which achieves vehicle classification by a real-time fast template matching, and the other colour band selection technique which exploits the colour properties of sequential video imagery to enhance the quality of templates. At present Colour band selection technique is implemented off line because of the amount of processing needed. There are more
comprehensive methods to exploit the colour properties of imagery, such as Principal Component Transform (Umbaugh et al. 1993) but these techniques require a large amount of computation and are not suitable for real-time applications running on low-cost systems. The proposed colour band selection technique within this work is comparable to the band selection criteria used in Colour Transformation Technique introduced by Ercal et al. (1993). The four classes of vehicle: car, van, lorry.1 (small lorry) and lorry.2 (large lorry) have been selected to test the performance of the fast template matching algorithm (without colour band selection). The templates for each class were generated interactively from an initial image sequence. The complete system has been tested offline using image sequences. It runs on a 500 MHz PC at 4 frames/sec. The algorithms introduced here are specifically tailored for use with static cameras, operating in scenes in which vehicles are assumed to follow fixed routes. Small changes of camera pan/tilt angles do not affect the template matching operations.

2. Template generation

For the first method (fast template matching without band selection) the templates are generated off-line by a human operator using a typical image sequence. In this application the images are RGB, and of size 768x576 pixels. The first step is to produce a background image by calculating the mean of first 20-30 images in the sequence. More elaborate background detection algorithms are possible (Toyama et al. 1999) but simple averaging is accurate enough in this case. The averaging is carried out incrementally as follows: Let $M(i,j)_{\text{curr}}$ be the current background image calculated from $k$ images. Let $F(i,j)_{\text{curr}}$ be the $k+1$ image. The value $M(i,j)_{\text{new}}$ of the $(i,j)$th pixel in the new background image incorporating $F(i,j)_{\text{curr}}$ is given by:

$$M(i,j)_{\text{new}} = \frac{k}{k+1} M(i,j)_{\text{curr}} + \left( \frac{1}{k+1} \right) F(i,j)_{\text{curr}} \quad 1 \leq i \leq m, \quad 1 \leq j \leq n. \quad (2.1)$$

The averaging is done separately for each RGB band. The calculation of the background image is initialised by setting $k=0, \quad M(i,j)_{\text{curr}}=0$.

The operator selects a region of interest in the image of size about 200x150 pixels, extending across the width of the road. When a suitable vehicle enters the region of interest a binary template for it is calculated as follows:

a) The background image and the current image are converted into grey level images $K, I_1$, respectively by averaging the RGB values for each pixel ($(R+G+B)/3$) (Jain et al. 1995; Bourke 1989).

b) The image $I_1$ is subtracted from $K$ to give the image $I(i,j)_{\text{subs}}$ defined by:

c) $$I(i,j)_{\text{subs}} = |I_1(i,j) - K(i,j)| \quad 1 \leq i \leq m, \quad 1 \leq j \leq n. \quad (2.2)$$

d) The image $I_{\text{subs}}$ is converted to a binary image $B$ by thresholding. The threshold value $T$ is selected manually by inspecting the histogram of the image. The histogram usually has two peaks and the threshold value is selected between them. This algorithm requires too much interaction with the operator.

$$B(i,j) = \begin{cases} 1 & \text{if } & I(i,j)_{\text{subs}} > T \\ 0 & \text{otherwise} & \end{cases} \quad (1 \leq i \leq n, \quad 1 \leq j \leq m) \quad (2.3)$$
An example binary image $B$ is shown in Figure 1. The templates are selected from $B$ by hand. A typical template is shown in Figure 3. Vehicle template data are in binary format and stored in the system video memory (VRAM) for real-time fast matching.

### 3. Template matching

Three types of template matching functions were considered: a) sum of absolute differences; b) normalised cross-correlation; c) sum of squared differences. Type (a), “sum of absolute differences” (Hussain 1991) was selected because it has a low computational cost, in contrast with (b), and because it does not overweight outlying values, in contrast with (c). Other more specialised template matching algorithms which are invariant to scale or orientation were not considered because of their high computational cost. The matching functions (a), (b) and (c) are shown in equations 3.1, 3.2 and 3.3 respectively. Here $F_{class}$ is a vehicle template and
\( F_{\text{blob}} \) is segment of a binary image obtained from a new image sequence. In (3.1)–(3.3) \( u \) is a pixel in the template and \( x+u \) is the corresponding image pixel.

Sum of absolute differences : \( A_1(x)_c = \sum_u |F_{\text{class}}(u) - F_{\text{blob}}(x + u)| \) (3.1)

Normalised cross-correlation : \( A_2(x)_c = P(x)/Q(x) \) where
\[
\begin{align*}
P(x) &= \sum_u F_{\text{class}}(u) F_{\text{blob}}(x + u) \\
Q(x) &= \sqrt{\sum_u (F_{\text{class}}(u))^2 * (F_{\text{blob}}(x + u))^2}
\end{align*}
\]

Sum of squared differences : \( A_3(x)_c = \sum_u [F_{\text{class}}(u) - F_{\text{blob}}(x + u)]^2 \) (3.3)

4. The Hardware and the data

The system consists of a Personal Computer with a relatively cheap processor (Intel Celeron 500 MHz), operating on a Windows NT platform. Image acquisition is by the Matrox Meteor II frame grabber, supported by the Matrox Mil-Lite 6.1 imaging library. The algorithms have been developed in MS Visual C++ which is the language supported by most imaging hardware products. The CCTV image sequences were obtained in VHS format, digitised by the Matrox frame grabber and converted to PAL format RGB image data (24-bit, 768x576 pixels) within the program to make processing easier.

5. Operation of the System

![Flow chart of vehicle classification algorithm](image-url)

Figure 4. Flow chart of vehicle classification algorithm
6. Results and discussions

As stated in section 2, templates are generated off-line by the user. The vehicle classes (car, van, lorry1, lorry2) and their templates are shown in Figure 5. The templates appear to be poorly structured because of the different illumination conditions and the variety of vehicle colours. However, the success of template matching depends on the similarity between the templates and the appropriate parts of the binary images. Successful matching is achieved because the binarisation used to obtain the template is similar to the binarisation of the test image sequence.

![Fig. 5. Vehicle classes (top) and their templates (bottom)](image)

6.1 System Performance

Table 1 shows the times for each complete loop operation, i.e., the times between two successive template matches, for the three template matching methods described at the beginning of Section 3. Even though one loop is dedicated only to one vehicle classification, the loop speed is fast enough in cases (a) and (c) to locate and classify almost all vehicles which enter into the region of interest. In case (b) the loop speed is extremely slow.

| Template matching technique | Car | Van | Lorry.1 | Lorry.2 |
|-----------------------------|-----|-----|---------|---------|
| a) Sum of absolute differences (difference measure) | 4.5 | 3.5 | 2.1 | 0.9 |
| b) Normalised cross-correlation | 0.6 | 0.5 | 0.3 | 0.1 |
| c) Sum of squared differences (difference measure) | 5.0 | 5.0 | 4.5 | 2.3 |

The confusion matrix (Huang et al. 1998; Kohavi and Provost 1998) contains information about actual and calculated classification results. In Table 2 the results are normalised and shown in percentage form. Actual classes in column 1 are matched against the same list of classes (in row 1) with the percentages of classification decisions shown. The success rate is calculated using ground truth identification of vehicles by the operator. For example, the figure of 85% in the second row and second column means that on being presented with an image containing a car the system chose the correct class, car, 85% of the time. The incorrect
class van is chosen 10% of the time, and the incorrect classes Lorry1 and Lorry2 are never chosen. The total numbers of vehicles counted during the classification experiment are shown in column 1. For the experiment a 6 minute video recording was used, containing approximately 1400 images.

### Table 2: Confusion matrix of vehicle classification results (with respect to sum of absolute differences method)

| Vehicle type (quantity) | Car (quantity) | Van (quantity) | Lorry.1 (quantity) | Lorry.2 (quantity) |
|-------------------------|----------------|----------------|-------------------|-------------------|
| Car                     | 85 %           | 10 %           | 0%                | 0%                |
| Van                     | 25%            | 83%            | 16%               | 0%                |
| Lorry.1                 | 0%             | 58%            | 85%               | 30%               |
| Lorry.2                 | 0%             | 50%            | 30%               | 98%               |

As vehicles enter the region of interest, they are classified and then highlighted automatically. A typical highlighted image is shown in Figure 6. The display is not always continuous due to variations in the loop speed of the classification algorithm.

![Fig. 6. System display of classification for a moving vehicle](image)

**6.3 System optimisation**

In real-time applications the major issues are low signal-to-noise ratio (SNR), unmodelled image data variations due to environmental illumination conditions or object features, insufficient system speed, etc. These problems have been investigated during the operation of the system and some optimisation of system components (hardware, software, data, methodology, etc) has been done as follows:

1. The size of the area of interest has been optimised to decrease computation time, subject to a minimum size constraint to ensure that the area can contain all types of vehicles (e.g. large lorries) as well as the width of the road.
2. RGB bands of the images have been selected to optimise the band combination, as described in Section 7.
3. Hardware has been selected to optimise between system cost and performance.
4. The software development has been achieved using a reduced version of the Matrox Mile-Lite imaging library which is almost 10 times cheaper than the full version.

7. Colour band selection technique

In a colour image the RGB band values depend on three major factors (Jain et al. 1995):

1. Spectral reflectance of scene surfaces
2. Spectral colour content of daylight illumination
3. Spectral response of the camera

In this application the first two factors change over time. These changes have major effects on vehicle blobs and sometimes lead to the generation of very poorly structured blobs. Some of the methods introduced in the literature (Ercal et al. 1993; Otha et al. 1980) exploit the colour properties of image RGB bands. Ercal et al compare their Colour Transformation Technique to Karhunen-Loeve (K.L.) transformation. As both methods use colour properties of images, their results are similar (82% of results differ by less than 9%). Otha et al. study the dynamic Karhunen-Loeve transformation and derive a set of effective colour features by systematic experiments in region segmentation. These techniques are based on the idea that in feature selection in pattern recognition theory, a feature is said to have large discriminant power if it has a large range of possible values (Ercal et al. 1993). Hence the consequent analysis is made over the image colour components to identify which of the colour bands has the best discriminating power for separating foreground (template) from the background.

The variance of each colour band is calculated as:

\[ v_r = \sum_{i,j} (r_F(i,j) - r_{BackGr}(i,j))^2 \]
\[ v_g = \sum_{i,j} (g_F(i,j) - g_{BackGr}(i,j))^2 \]
\[ v_b = \sum_{i,j} (b_F(i,j) - b_{BackGr}(i,j))^2 \]

(7.1)

Here \( \{v_r, v_g, v_b\} \) is the vector of distributions of R, G, and B of foreground (F) and background (BackGr) sample areas, which are selected in both background and foreground regions. Our proposed colour band selection technique is based on the image contrast ratio between foreground and background. It is quite simple and does not require large computation. Like the methods used by Ercal et al. (1993) and Otha et al. (1980), it makes use of colour components of each band and selects the best one depending which one contains the most information (higher variance). The aim of colour band selection technique is to find the most suitable band of RGB values for which well formed vehicle silhouettes can be obtained. The technique works in the following manner:

1. Subtract the current image \( F_{1RGB} \) from the background image \( M_{RGB} \) for each Red, Green and Blue band separately and take absolute values. In (7.2) the corresponding colour bands (RGB) of both images are subtracted separately as: \( (R_1, G_1, B_1) - (R_2, G_2, B_2) = (R_s, G_s, B_s) \) and absolute values \( |R_s|, |G_s|, |B_s| \) are calculated pixel by pixel.

Hence, the absolute pixel values of the difference images \( dF_{RGB} \) for each band are defined by:

\[
|R_s| = |M(i,j)_{Red} - F(i,j)_{Red}| \quad 1 \leq i \leq m, 1 \leq j \leq n \\
|G_s| = |M(i,j)_{Green} - F(i,j)_{Green}| \\
|B_s| = |M(i,j)_{Blue} - F(i,j)_{Blue}| 
\]

(7.2)
2. Calculate average pixel values for each $|R_\delta|$, $|G_\delta|$ and $|B_\delta|$ over the region of interest ($nxm=200x150$ pixels) in difference images (dF_{RGB}): 

$$
|R_\delta|_{\text{aver}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} |dF(i, j)_R|}{nxm},
|G_\delta|_{\text{aver}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} |dF(i, j)_G|}{nxm},
|B_\delta|_{\text{aver}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} |dF(i, j)_B|}{nxm}
$$ (7.3)

3. Select the most dominant band, i.e. the one for which $|R_\delta|_{\text{aver}}$, $|G_\delta|_{\text{aver}}$, $|B_\delta|_{\text{aver}}$ is the largest. The most dominant band is the most suitable one for template matching because it gives the highest contrast between the background and the foreground (current image). In typical cases the contrast can be 30 units or higher. The band selection is made for every second image, and the template matching is carried out on the intervening images. The flow diagram is shown in Figure 7. The improvement in vehicle blob quality achieved by selecting the dominant band is shown in Figure 8, which shows a 244% improvement of blob quality which is derived from enlargement of blob area (white pixels). This result has been concluded by the ratio of pixel quantities (counted) in both templates (3 and 4, in Figure 8). The results of the proposed technique are also compared with the results yielded by Colour Transformation Technique (CTT) (Ercal et al., 1993). For comparison test, a set of three vehicles is used (Figure 9) and the results are presented in Table 3. The advantage of the proposed technique over CTT is that it calculates the most suitable band automatically, whereas in CTT a sample area in the template is selected manually by hand since it is difficult to estimate the exact shape and location of template during the automated process. Other similar techniques like Karhunen-Loeve were not investigated because they require costly computation and would be non-practical for the real-time applications.

![Fig. 7. Adaptive colour adjustment flow diagram](image-url)
Colour band selection technique selects the most appropriate band considering the colours of the vehicle and the image background. Some illumination effects which lead to colour variations on vehicles are not considered for band selection process. All calculations are made with reference to the dominantly visible colour of the vehicle. The set of vehicles for the comparison test between colour band selection technique and Colour Transformation Technique (CTT) is shown in Figure 9, and the test results are shown in Table 3. The similarity of results between both methods (for the most suitable band selection) may be seen in Table 3. Figure 10 also confirms the result that the most suitable band for Car 1, is Red. These experiments show that colour band selection technique can be used as efficiently as Colour Transformation Technique for fast band selection in the real-time applications.
As it is seen  the quality of  images is degraded by image interlacing effect.

Table 3. Comparison between two methods of band selection (the selected most suitable bands are highlighted)

| Vehicle Type  | Adaptive Colour Adjustment Technique | Colour Transformation Technique (normalised values as $\frac{V_l}{(R+G+B)}$) |
|---------------|--------------------------------------|---------------------------------------------------------------------|
|               | Red        | Green | Blue | Red | Green | Blue |
| Car 1 (yellow)| **75.15**  | 73.06 | 3.12 | **0.35** | 0.34 | 0.31 |
| Car 2 (white) | 80.98      | **90.01** | 89.97 | 0.32 | **0.35** | 0.33 |
| Fire engine (red) | 36.51      | 45.13 | **52.52** | 0.22 | 0.32 | **0.45** |

Figure 10. Difference images of Car 1 in Red, Green and Blue bands respectively obtained by Formula 7.1. The Red band is selected as most suitable one.

9. Conclusion

The system described in sections 2-5 solves the conventional template matching algorithm problem for real-time operation. The main issue of poor condition and structure of vehicle blobs has been related to inefficient colour band combination and a technique has been developed called colour band selection technique which has improved the vehicle blobs, as shown in Figure 8 and 10. Some further research is to be carried out to improve both template matching criteria and the shapes of the vehicle blobs.

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*The Author was at University of Reading