Refined Gaussian Weighted Histogram Intersection and Its Application in Number Plate Categorization

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Abstract

This paper proposes a refined Gaussian weighted histogram intersection for content-based image matching and applies the method for number plate categorization. Number plate images are classified into two groups based on their colour similarities with the model image of each group. The similarities of images are measured by the matching rates between their colour histograms. Histogram intersection (HI) is used to calculate the matching rates of histograms. Since the conventional histogram intersection algorithm is strictly based on the matching between bins of identical colours, the final matching rate could easily be affected by colour variation caused by various environment changes. In our recent paper [9], a Gaussian weighted histogram intersection (GWHI) algorithm has been proposed to facilitate the histogram matching via taking into account matching of both identical colours and similar colours. The weight is determined by the distance between two colours. When applied to number plate categorization, the GWHI algorithm demonstrates to be more robust to colour variations and produces a classification with much lower intra-class distance and much higher inter-class distance than previous HI algorithms. However, the processing speed of this GWHI method is still not satisfying. In this paper, the GWHI method is further refined, where a colour quantization method is utilized to reduce the number of colours without introducing apparent perceptual colour distortion. New experimental results demonstrate that using the refined GWHI method, image categorization can be done more efficiently.

Keywords—**Refined Gaussian weighted histogram intersection, Number plate categorization, Colour quantization, Colour variations**.

1. Introduction

Using colour histogram as a stable representation over change in view for object recognition was explored by Swain and Ballard [1][2]. They introduced the colour indexing technique to efficiently recognize objects by matching their colour histograms via histogram intersection (HI) method. This algorithm did not address the issue of illumination variation.

Towards an illumination-insensitive histogram-based image matching algorithm, many alternations have been suggested. These methods can be roughly divided into two groups.

The first group, instead of using colour directly, aims to generate histograms from other colour-generated features. This includes Funt et al.'s [3] ratio of colour RGB triples, and Nayar et al.'s [4] colour reflection ratios. Gevers et al. [5], Jia et al. [6] and Zhang et al. [7] further developed the colour ratio gradient to make it less sensitive to the geometry and position of the object, shadows, illuminations, and other imaging conditions.

The second group tries to improve the definition of the histogram intersection which is used to measure the matching degree of two histograms. Wong et al. [8] proposed a merged-palette histogram matching (MPHM) method. Using their method, two perceptually similar colours, instead of identical colours, can be intersected.

The idea proposed in our recent paper [9] belongs to the second group. Note that, in the MPHM method, the weight, describing the contribution of a set of similar colours used to matching the given colour, is the same. This however does not well reflect the matching contributed by different colours. In this paper, we propose a Gaussian-weighted histogram intersection (GWHI) algorithm, where a weight function is used to differentiate the contributions by different colours.

The proposed GWHI algorithm is applied to number plate categorization. During our previous research on automatic number plate detection [10], it is found that there are different classes of number plates with quite different features. Our aim is to differentiate number plates which belong to different categories for the benefit of further detection and recognition task. Due to variant environment under which the number plate images were taken, there are unavoidably big variations between number plates of same classes in colour. A feature and a corresponding matching method robust to colour variation are hence essential.

Since the GWHI proposed in [9] needs to scan full colour space in order to compute the matching between two colour histograms, it usually takes longer time to compute the matching rate. This processing speed is apparently unsatisfactory for practical use. In this paper, the GWHI method is further refined to improve its processing speed. The number of colours is reduced greatly by using Wu's [11] colour quantization method without introducing apparent perceptual colour distortions. Using the refined GWHI method, image matching can be done much faster than using GWHI method and previous HI methods. Since the colour quantization method used for this refinement does not introduce apparent perceptual colour distortions, the matching using the new method still keeps all advantages of the GWHI method.

The remaining parts of the paper are organized as follows. The previous HI methods are introduced in Sect. 2. In Sect. 3, Gaussian weighted HI and its refined counterpart is presented in details. In Sect. 4, the proposed algorithm is tested and the experimental results are shown and compared with the conventional HI and the MPHM methods. The paper is concluded in Sect. 5.

2. Previous Histogram Intersection Methods

Histogram-based image matching algorithms try to measure the similarities in contents via their histograms between a model image and any images in database, i.e., target images, in order to properly classify images. Histogram intersection (HI), proposed by Swain and Ballard [1][2], is a straightforward method to calculate the matching rate of two histograms for this purpose.

2.1. Histogram intersection (HI)

Assuming the histograms of the model image and target image are H_M and H_T respectively, and each contains n bins, Swain and Ballard [2] defined the intersection, denoted by HI, of two histograms as:

$$HI = \sum_{i=1}^{n} \min\left(h_M(i), h_T(i)\right), \qquad (1)$$

where both H_M and H_T are normalized to the range of [0, 1] by the total number of pixels in images.

It can be seen that the resultant fractional matching value between 0 and 1 is actually the proportion of pixels from the target image that have corresponding pixels of the same colour in the model image. A higher matching rate indicates a higher similarity between two images.

2.2. Problems with existing HI algorithms

The conventional HI algorithm has a limitation due to the fact that it assumes identical colour matching, i.e., only corresponding bins of identical colours can be matched. In practice, however, the colours of real world images can be distorted both in the scene itself and in the image capturing process. Hence, images with same visual information but with different colour intensity may degrade the similarity level significantly when the conventional HI method is used.

Note that in the conventional HI method, the RGB-based histogram is investigated. However, images with same chroma information but with shifted lightness may degrade the similarity level significantly [8]. An intuitive solution to this problem is to obtain histograms based on other colour space. It can be easily testified that using other colour spaces, such as normalized rgb, which is believed to be simple and robust to intensity changes of colours, still cannot address this kind of colour variations.

Another problem associated with the conventional HI method is its heavy computation load. Assume the total number of possible colours in the model image is N_C. So, there are N_C bins in the colour histogram of the model image. Without loss of generality, we assume that there is same number of colours in the target images. If the colour sets of two images are identical, a single bin-to-bin comparing is enough. Thus the minimum number of comparison operations between two colour histograms will be N_C. However, if two colour sets are different, for each bin in the model colour histogram, each bin of the target colour histogram needs to be searched and compared. Thus, there will be at least $(N_C)^2$ comparison operations in order to work out the similarity between two colour histograms. It is known that the total number of colours for a 24-bit true-colour image is $N_C = 2^{24}$. Without reducing the number of colours, it is unlikely that the histogram comparison operation could be executed in real-time with such a tremendous dimension.

In order to overcome these problems, Wong et al. [8] proposed a merged-palette histogram matching (MPHM) method. The essence of the method is to extend the intersection from bins of identical colours to bins of similar colours. In their algorithm, as long as the distance between two colours is less than a fixed threshold, the intersection between the bins of these two colours will be calculated. This algorithm has produced more robust image retrieval results for images captured under various illumination conditions. However, it assumes an identical weight of the contribution between colours which have different similarities with the given colour. When applied to number plate image matching, the algorithm still exhibited to be sensitive to colour variations.

In our recent paper [9], a Gaussian weight function is utilized to differentiate the contribution between colours which have different distance to the given colour. This new histogram intersection method is called Gaussian Weighted Histogram Intersection, abbreviated as GWHI. In order to improve the matching speed, in this paper the GWHI is further refined by reducing the number of colours without introducing dramatic perceptual distortion.

3. Refined GWHI method

3.1. GWHI

Let us denote the distance between two colours $\vec{C}_1$ and $\vec{C}_2$ as $\left\|\vec{C}_1 - \vec{C}_2\right\|$, and the weight as $w\left(\left\|\vec{C}_1 - \vec{C}_2\right\|\right)$, which is a function of the distance between two colours. A generalized histogram intersection can be written as:

$$HI = \sum_{i=1}^{n}\sum_{j=1}^{n} \min\left(h_M(\vec{C}_i), h_T(\vec{C}_j)\right) \cdot w\left(\left\|\vec{C}_i - \vec{C}_j\right\|\right) \quad (2)$$

With this definition, the weight function in the conventional HI and the MPHM corresponds to:

$$w\left(\left\|\vec{C}_i - \vec{C}_j\right\|\right) = \begin{cases} 1 & \text{if} \left\|\vec{C}_i - \vec{C}_j\right\| \le Th \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where Th is zero for the conventional HI algorithm and a non-zero constant for the MPHM algorithm.

Instead of assigning identical weight for each colour as long as they fall in the range of bandwidth, a Gaussian function is applied to describe the relationship between the colour distance and its contribution to matching as:

$$w\left(\left\|\vec{C}_i - \vec{C}_j\right\|\right) = \begin{cases} f\left(\left\|\vec{C}_i - \vec{C}_j\right\|\right) & \text{if} \left\|\vec{C}_i - \vec{C}_j\right\| \le BW \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where BW is the bandwidth of the weight function and the Gaussian function $f(x)$ is:

$$f(x) = \frac{A}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad -\infty < x < \infty . \quad (5)$$

In our practice, for simplifying computation purpose, we take 99.9% energy to approximate the total energy in the infinite space and truncate the tail of the Gaussian function. Note that for a Gaussian function, when $x^* = 3.3\sigma$, we have:

$$\int_{-x^*}^{x^*} f(x)dx = 99.9\% \int_{-\infty}^{\infty} f(x)dx . \quad (6)$$

So, the bandwidth of Gaussian function is $BW = 3.3\sigma$.

The definition of colour distance is measured by the perceptual difference as:

$$\left\|\vec{C}_1 - \vec{C}_2\right\| = \sqrt{(l_1 - l_2)^2 + (u_1 - u_2)^2 + (v_1 - v_2)^2} \quad (7)$$

where $\vec{C}_1 = (l_1, u_1, v_1)$ and $\vec{C}_2 = (l_2, u_2, v_2)$ are two colours represented in *CIEluv* colour space. l takes a value in the range of $[0,100]$, u takes a value in the range of $[-83,175]$, and v takes a value of $[-134,107]$. The detailed conversion from *RGB* to *CIELuv* colour space can be found in [12] (pp. 110). In experiments, the reference white is set at $(R,G,B) = (255,255,255)$.

3.2. Reducing number of colours

Reducing the number of colours in images is essential in order to match histograms in real-time via HI method.

The colour number reducing operation is also called *colour quantization* in references. In [5], colour quantization was simply performed in the RGB colour space using a k-means nearest neighbour algorithm. However, the RGB colour space is known to be sensitive to colour variations. Furthermore, the appearance of the colours of an object may differ significantly from image to image because of illumination variations, perceptual colour surround effects, and so forth [6]. The quantization must be designed carefully to ensure that perceptually similar colours are mapped to the same quantized colour values. As its consequence, in [6] a perceptual colour naming method was employed in order to handle colour variations. The standard ISCC-NBS Colour Names Dictionary was employed to quantize and name the colour space. Each of the pixels is assigned to the standard *name* of the closest ISCC-NBS centroid colour, according to the Euclidean distance in *CIELab* colour space. This method uses a single colour set for all images and the histogram comparison can thus be performed on a bin-to-bin base. However, since the colours of compound colour objects, such as car number plates, only take a very small part of the standard colour set, such quantizing methods usually cause large perceptible colour distortions. As explained earlier in Section 2, however, the identical bin-to-bin matching cannot address matching between distorted colours.

In this paper, Wu's [11] optimal colour quantization algorithm, which is based on variance minimization, is employed to reduce the number of colours by introducing only slight colour distortion into the quantized images. Fig. 1 gives examples of the quantized images and their original images.

Fig. 1 Two images (left column) and their quantized counterparts (right) using variance minimization algorithm with eight colours.

Since the interested objects in this research take very limited number of colours, each image can be quantized into a fixed small number of colours while introducing only slight distortion based on the variance minimization rule. Eight colours and sixteen colours have been experimented. Since using sixteen colours did not make many improvements for image matching results, each image is quantized into eight colours using the Wu's algorithm. Obviously, the resultant colour set contained in each image depends on its original colour distribution before colour quantization.

3.3. Refined GWHI

Since the interested objects in the research, colour number plates, are compound colour objects, which perceptually take very limited number of colours, in order to improve the speed of computing, each image is firstly quantized into eight colours with only slight perceptual distortion introduced.

After colour quantization, there will be a short colour mapping table (also called *palette* or *look-up table*) in each image file, which contains colours that are used in current image. The data in the quantized image file only record the index of the colour in the colour table, rather than its detailed colour information. Thus, the colour histogram only contains eight bins with each bin representing a colour index.

When used to compute matching of two histograms, in order to compute the distance between two colours, of which each corresponds to a bin in their histograms, the colour value represented in *CIELuv* colour space should be employed. Thus the colour table needs to be carried with each quantized colour image to record the mapping relationship from each colour index to its corresponding colour value.

By this way, in our experiments, the total number of comparisons between two colour histograms is reduced to $8^2 = 64$. This improves the computation efficiency of the histogram matching greatly while satisfactory results can still be produced.

4. Experiments

The proposed method is applied to categorize car number plate images into proper classes based on their colours. The aim is to find a robust classification between different classes of number plate images. Number plates are viewed to belong to the same class when they have similar foreground and background colours, but they may have quite different contents (characters), size and viewing conditions. Two classes of number plates are frequently used in NSW, Australia. Without loss of generality, images of the two classes of number plate are tested, namely, plates with yellow background, denoted by *YELLOW plates*, and plates with white background, denoted by *WHITE plates*. In each group, a typical image is firstly selected manually as the model image. Histograms of other images to be categorized are then computed and matched with the histograms of two model images. Plate images are categorized to the group of which the image has a higher matching with the model image.

4.1. Experiment setup

A yellow number plate image is selected as the YELLOW model image, and a white number plate image is selected as the WHITE model image. The selection of model images is basically random. The selection criterion is that the selected model images are neither too bright nor too dark compared with other images to be categorized. The two model images and some examples of yellow and white target images are shown in Fig. 2 and Fig. 3 respectively. It can be seen that, due to various environment changes, images that belong to same class may still have quite different appearances.

In order to compare experimental results obtained with three methods, all histogram matching are computed in *CIEluv* color space. For this purpose, color histograms are firstly collected in RGB colour space. Three histogram intersection methods mentioned in Sect. 3 are then applied to compute the matching rates between histogram of each target image to the histogram of model image. During all matching, colours represented by each bin are firstly converted to *CIELuv* colour space. Then, colour distance is computed in regard to the *l*, *u* and *v* values. In the refined GWHI method, however, before collecting the colour histogram of each image, images represented in full colour space is firstly quantized into eight colours using Wu's colour quantization algorithm.

(a) Yellow model image

(b) Yellow target images

Fig. 2 Examples of yellow number plates.

(a) White model image

(b) White target images

Fig. 3 Examples of white number plates.

Furthermore, the parameter σ in our method in (5) can be selected empirically. In order to compare experimental results with those of the MPHM algorithm, following restrictions are set on selection of σ :

(1) $f(x)_{|x=0} = 1$;

(2) $\int_{-\infty}^{\infty} f(x)dx = 2Th$; and

(3) Using $99.9\%\int_{-\infty}^{\infty} f(x)dx$ to approximate $\int_{-\infty}^{\infty} f(x)dx$.

where *Th* is the threshold set in the MPHM method. Condition (1) sets the contributions of identical colours in two methods as the same. Condition (2) and (3) makes sure the overall weights between two different methods are approximately same.

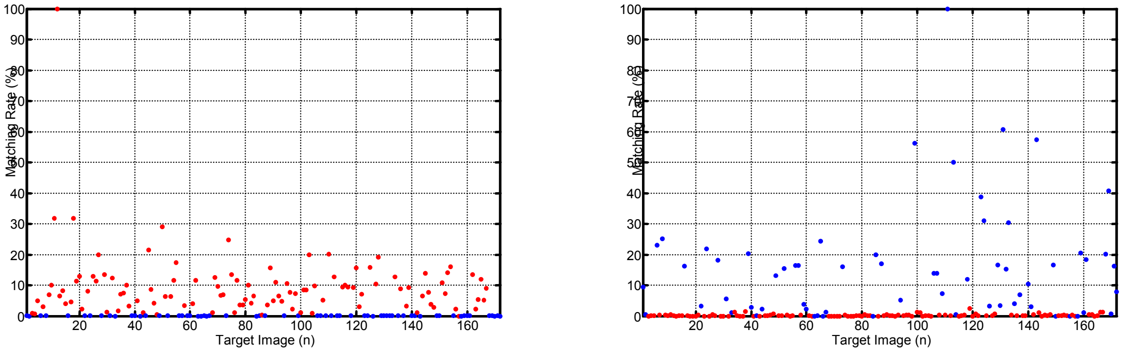
It can be worked out from Condition (1) that

$$\frac{A}{\sqrt{2\pi}\sigma} = 1 . \tag{8}$$

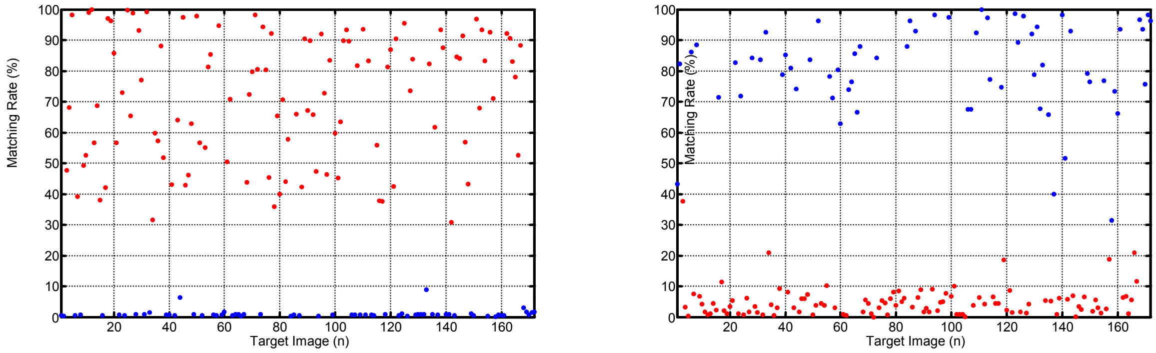
From Conditions (2) and (3), it can be worked out that,

$$0.999A = 2Th . \tag{9}$$

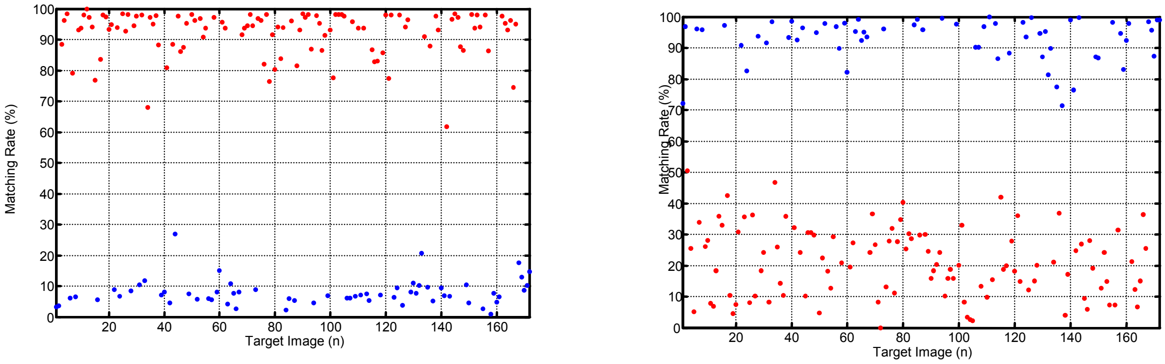
From Eq. (8) and (9), it can be derived that



(a) Matching results obtained using the conventional HI method.



(b) Matching results obtained using the MPHI method.



(c) Matching results obtained using the proposed GWHI method.

Fig. 4 Histogram matching results obtained using three histogram intersection methods. Matching data of yellow number plate images are marked as red dots, and matching data of white number plate images are marked as blue dots. Left column are the matching results with the yellow model image; right column are the matching results with the white model image.

$$\sigma = \frac{2}{0.999\sqrt{2\pi}} Th \doteq 0.8Th .$$

Thus, we have $BW = 3.3\sigma \doteq 2.633Th$, and Eq. (5) is

$$f(x) = \exp(-\frac{x^2}{2\sigma^2}), \ -2.633Th <= x <= 2.633Th , \quad (10)$$

where $\sigma \doteq 0.8Th$. The bandwidth Th in experiments is set as $Th = 15$, which is the same as in [8]. Thus, we have $\sigma \doteq 12$ and $BW \doteq 40$.

4.2. Experimental results and discussion

The colour histograms of the model images, in *CIEluv* colour space, are computed and matched with those of total 172 number plate images, including 109 yellow plates and 63 white plates.

Using the refined GWHI method, the average time needs for matching two number plate images with dimension of 120×40 is 11 milliseconds. Compared with the average time of 2.035 seconds using the GWHI method, 0.935 seconds using the MPHM method, and 1.081 seconds using the conventional HI method, this processing speed is 185 times, 85 times, and 95 times faster respectively. All data are tested on a computer with Intel Pentium IV 1.8GHz CPU and 380MB of RAM.

The matching results are plotted in Fig. 4, where matching data of yellow plates are painted in red dots and white plates in blue dots (darker if viewed in black-white picture).

As seen in Fig. 4(a) that, using the conventional HI method, it is impossible to separate two classes of number plate images via their colour histograms. Actually, even though the matching rates of number plates from different classes are very low, the matching rates of the number plates from same class may also be as low as 0.00%.

Using the MPHM method, it can be seen from Fig. 4(b) that this problem has been improved a lot. As shown in the figures, the distance between the matching rates of inter-class number plates have been increased greatly. However, though using MPHM can separate two classes given that a proper threshold is carefully selected, the matching rates of same class are still very sensitive to colour variations. As shown in the figure, the matching data of intra-class plates still spread in a wide range.

Using our proposed GWHI method, it can be seen in Fig. 4(c) that, although all matching rates have increased to some extent, it is more easily to categorize two classes of number plates based on the matching to the model images. The intra-class distance of the matching becomes smaller and the inter-class distance becomes larger. This is due to the fact that a wider bandwidth has been used than in the MPHM method. At the same time, the matching rates of number plates from same class are much more stable compared to the results obtained using the HI and MPHM methods. This is because a weight function is employed rather than simply adding up all intersections from different colours. Even though the matching rates of different class of plates have increased at the same time, the distance between two classes becomes larger. This leads to a more confident and easier categorization.

5. Conclusions

In this paper, a refined Gaussian weighted histogram intersection (GWHI) method is proposed and applied for number plate categorization. A Gaussian function is used to weight the contribution to the matching by the colors which have different distance with the given color. Our aim is to categorize number plate images into two classes, plates with perceptually yellow background and plates with perceptually white ground. By using the variance minimized colour quantization method to reduce the number of colours, the image matching is much faster than the GWHI algorithm and previous HI algorithms, while satisfactory categorization results can still be produced. Experimental results show that using the refined GWHI method, there are following benefits: (1) the intra-class distance becomes much smaller; (2) the inter-class distance becomes much larger; and (3) the algorithm is much faster than previous histogram-based methods. In conclusion, the matching of color histogram using the refined GWHI method is less sensitive to color variation and faster than previous HI methods.

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