J. Shanghai Jiaotong Univ. (Sci.), 2011, 16(4): 395-401
DOI: 10.1007/s12204-011-1167-7

An Information-Based Color Feature Representation and Its Application in Detecting Adult Images

Shi-Lin Wang[†, 1] and Alan Wee-Chung Liew[#]

[†]*School of Information Security Engineering, Shanghai Jiaotong University, Shanghai, CHINA*

[#]*School of Information & Communication Technology, Gold Coast Campus, Griffith University, QLD 4222, Australia*

[1] Corresponding author. Tel.: +8621-6293-2969; Fax: +8621-6293-2969.

E-mail addresses: wsl@sjtu.edu.cn (Shi-Lin Wang), a.liew@griffith.edu.au (Alan Wee-Chung Liew).

Abstract: For many image classification tasks, color histogram is usually employed as an important "signature" to describe the color distribution of the image and infer the image content. However, most traditional color histograms cannot achieve satisfactory results in many image classification systems. In order to improve the accuracy and reduce the computational complexity of the classification task, an information-based color feature representation is proposed in this paper. The mutual information between the feature and the class label is adopted to evaluate the discriminative power of the feature. A novel quantization scheme is presented, which removes the redundant color components and combine the adjacent components together to generate a new feature to maximize the discriminative ability. An iterative algorithm is performed to derive the color space quantization and color feature generation. In order to illustrate the effectiveness of the proposed color representation, a specific image classification task, i.e., differentiating the adult images from benign ones, is employed. Experimental results show that our color feature achieves better classification performance and better efficiency compared with the traditional color histogram.

Keywords: Color histogram, mutual information, image classification

1. Introduction

Color histogram is usually adopted as the image signature in many image retrieval and image classification tasks. It reflects the color distribution of an image and is invariant against translation, rotation and scaling (with proper normalization). The color histograms are constructed by the following progression: i) color space selection; ii) color space quantization; iii) counting the number of pixels of each color.

In recent years, many researchers have proposed various color histograms for image classification and image retrieval [1-5] and the major difference among these methods is the quantization scheme. The rectangular-shape binning [2] is one typical quantization method, which is generated by dividing the entire color space into a number of cubic bins and counting the number of pixels in each cubic bin. Uniform quantization is the traditional and widely used method; however, non-uniform quantization according to the characteristics of the color space shows superiority performance in many image classification and retrieval applications [1-3]. However, as the histogram bins are constrained to be of rectangular shape, the color distribution may not be efficiently described. To overcome such difficulty, the clustering-based histogram generation methods have been proposed [4]. The clustering methods usually divide the color space into a large number of bins and then group them by a clustering algorithm such as the *k*-means [4]. Recently, Wee Kheng Leow and Rui Li [5] have extended the clustering-based histogram and proposed the adaptive-binning color histogram. They perform clustering to the color distribution for an image rather than the entire color space and thus different color space partition is derived for different images.

The color histograms mentioned above can serve as the color information description for many image classification tasks. However, most of them usually cannot provide accurate results due to: i) the appropriate color resolution is hard to determine; ii) the quantization scheme does not related to the target image categories and thus some histogram bins contain discriminating information for classification while others do not; iii) the intrinsic relationship among the histogram bins cannot be inferred from the histogram. Moreover, for the adaptive-binning color histogram, the histogram quantization and the distance (or dissimilarity) calculation between two different histograms needs much more computation compared with those of fix-binning ones.

In order to solve the above difficulties in image classification by color histograms, a new information-based color representation is proposed. Compared with the traditional color representations, the proposed color histogram has the following advantages and is more suitable for the image classification task: i) the quantization scheme is based on the particular color distribution of the images being classified, i.e., the redundant bins are discarded and the discriminative bins are preserved; ii) a linear combination of the adjacent bins is employed to exploit the intrinsic relationship among these color components; iii) the mutual information (MI) [6] is adopted to comprehensively evaluate the discriminative power of each histogram component and the Renyi's formulation of MI [8] is employed to reduce the computational complexity.

The paper is organized as follows. In section 2, the deficiencies of the traditional color histograms for image classification are demonstrated. Section 3 introduces the definition and derivation of the proposed color representation. The evaluation of the discriminative power of a specific feature set based on the information theory is also presented in this section. The experimental results and discussions on the experiments are shown in section 4. And finally section 5 draws the conclusion.

2. Difficulties of image classification by the color histograms

Since they are easy to compute and tolerate against the small changes of the view points, the traditional color histograms are widely used in image retrieval and classification. However, for the image classification task, most of the color histogram techniques may not achieve satisfactory results. In order to explicitly demonstrate the difficulties of employing the color histogram in image classification, a particular image classification task of differentiating the adult images from the benign ones is adopted for illustration.

The image dataset for evaluation is composed of two thousand images (200 adult images and 200 benign ones) collected from the Internet. The $10 \times 10 \times 10$, uniformly quantized color histogram is adopted to describe the color distribution of these images. Fig.1 demonstrates the two statistical properties, mean and standard deviation, of the color histogram. In order to clearly present the color distribution, the 3D histogram is extended to ten 2D representations. From Fig.1, it can be observed that: i) First, not all the color components contain useful information about the image content. There are many components with very small mean and std. values, which shows that such color seldom appears in natural images; Second, some components have similar mean value for different image class while others not, which demonstrates that different color component has different discriminative power for classification. Due to the above two issues, the traditional color histograms cannot achieve satisfactory result for the image classification task. For the rectangular-shaped histograms, empty bins are inevitable unless the color resolution are greatly reduced (which may also reduce the classification accuracy). The clustering-based histograms may solve the problem of empty bins and represent the images more efficiently. However, neither of them can handle the second issue because the quantization scheme of these methods aims to better represent the color information for the entire image set rather than to provide more discriminative information for differentiating various image classes.

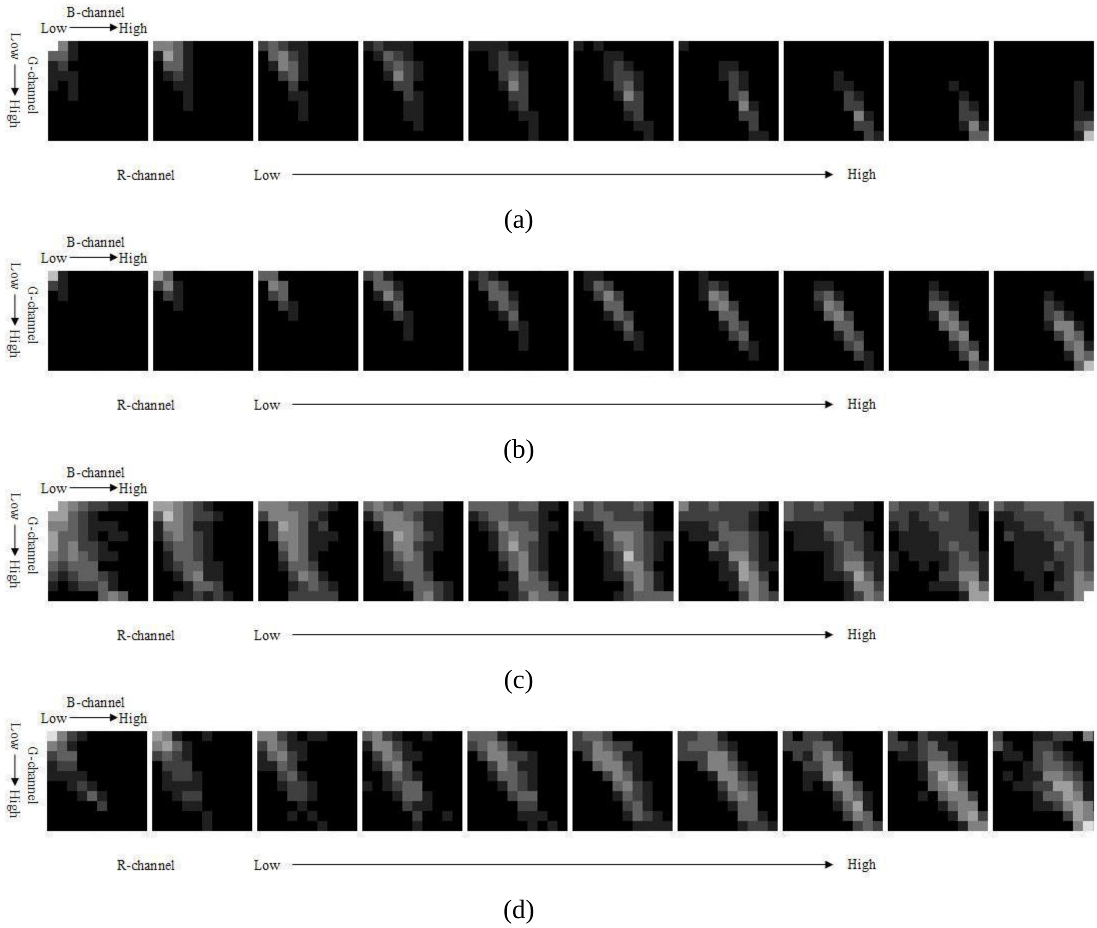


Fig.1 The color distribution of the adult images and benign ones: (a) (c) the mean and standard deviation of the benign images; (b) (d) the mean and standard deviation of the adult images. The higher luminance represents the larger value of the color component.

Another important issue which prevents the traditional color histograms from achieving accurate classification results is that the relationship between adjacent color components is omitted for these methods. Considering such relationship may introduce more discriminative information for image classification. Mutual information (MI) between the value of the color component(s) and the class label is adopted to evaluate the discriminative power of the component(s). Since the color components with too low discriminative power are redundant in classification, only those components with MI value greater than 0.1 are investigated. In order to demonstrate the effectiveness when introducing the neighbouring relationship, three situations have been considered: i) the original color component; ii) both the original and the neighbouring color components; iii) combing the original and the neighbouring color components into a new color component. Table 1 listed the results of discriminative power analysis.

	Situation i	Situation ii	Situation iii
Normalized MI	0.65	0.97	0.69

Table.1 Discriminative power analysis

It should be noted in Table.1 that i) the original component is always of higher MI value than the neighbouring one such that duplicated computation is avoided; ii) the MI value is normalized by dividing the summation MI value of the original and the neighbouring components; iii) the normalized MI given in the table is the average value of all the discriminative color component pairs. From Table.1, it can be observed that exploiting the relationship among adjacent color components may increase the discriminative power for classification. However, most traditional color histograms do not take such useful information into account.

3. **The proposed color representation**

In order to solve the difficulties mentioned in Section 2, an information-based color histogram is proposed to represent the color information for image classification. First, a high resolution uniform-quantized color histogram is derived to guarantee sufficient color depth. Then Renyi's MI formulation is adopted to evaluate the discriminative power of each color component accurately and efficiently. A linear transform is performed to not only reduce the dimensionality of the histogram but incorporate the relationship information among adjacent color components as well. Finally, an iterative approach is employed to derive the quantization method and the information-based color histogram as well.

3.1 Information-based Discriminative Power Evaluation

In order to obtain an efficient color space description, each component of the color representation should be discriminative. However, how to describe and compute the discriminative power of a component (or a set of components) is an important issue. Recent research shows that the mutual information (MI) between the class label and the feature can be a general criterion to represent discriminative power of the feature [7]. The major advantages of MI are i) it is invariant to the classifier selection; ii) it accounts for high-order statistics so that non-linear relationship between the feature and the class label can be well-represented by MI. However, high computational complexity of Shannon's MI prevents it from being widely used currently. Recently, Principe et al. [8] present how using Renyi's formulation rather than Shannon's leads to non-parametric entropy estimators when coupled with Parzen density estimation. Then Torkkola [9] gives a formulation of MI between the continuous variables and discrete class labels. With continuous-value Y and discrete class label C, the mutual information is as follows [9]:

$$I(C,Y) = V_{IN} + V_{ALL} - 2V_{BTW} = \sum_c \int_{\mathbf{y}} p(c,\mathbf{y})^2 d\mathbf{y} + \sum_c \int_{\mathbf{y}} P(c) p(\mathbf{y})^2 d\mathbf{y} - 2\sum_c \int_{\mathbf{y}} p(c,\mathbf{y})^2 P(c) p(\mathbf{y}) d\mathbf{y} \tag{1}$$

With the assumption of Parzen distribution for $P(y)$ and $p(c, y)$, three terms in (1) can be rewritten as follows.

$$V_{IN} = \sum_c \int_{\mathbf{y}} p(c,\mathbf{y})^2 d\mathbf{y} = \frac{1}{N^2} \sum_{p=1}^{C} \sum_{j=1}^{N_p} \sum_{k=1}^{N_p} G(\mathbf{y}_{pj} - \mathbf{y}_{pk}, \sigma^2 \boldsymbol{I}) \tag{2}$$

$$V_{ALL} = \sum_c \int_{\mathbf{y}} P(c) p(\mathbf{y})^2 d\mathbf{y} = \frac{1}{N^2} \left(\sum_{p=1}^{C} \left(\frac{N_p}{N} \right)^2 \right) \sum_{j=1}^{N} \sum_{k=1}^{N} G(\mathbf{y}_j - \mathbf{y}_k, \sigma^2 \boldsymbol{I}) \tag{3}$$

$$V_{BTW} = \sum_c \int_{\mathbf{y}} p(c,\mathbf{y})^2 P(c) p(\mathbf{y}) d\mathbf{y} = \frac{1}{N^2} \sum_{p=1}^{C} \frac{N_p}{N} \sum_{j=1}^{N_p} \sum_{k=1}^{N} G(\mathbf{y}_{pj} - \mathbf{y}_k, \sigma^2 \boldsymbol{I}) \tag{4}$$

where C is the total number of classes, N_p and N are the number of training samples in class p and the total number of training samples respectively. G is the Gaussian kernel and σ is the kernel width.

For a single feature, y is one dimensional and the MI value can be calculated directly. For a feature vector, a dimension-reducing linear transformation is performed to project the feature vector x onto a single value with the maximum MI value. Thus,

$$\boldsymbol{w} = \arg\max_{\boldsymbol{w}} (I(C,Y)); \quad \boldsymbol{y} = \boldsymbol{w}^{\boldsymbol{T}} \boldsymbol{x} \quad \text{subject to } w^T w = 1 \tag{5}$$

As directly calculate w in (5) is difficult, an iterative optimization method is adopted. The linear discriminant analysis (LDA) is performed on the training set to derive the initial estimate of the weighting parameter vector, $w_{initial}$. According to the partial derivatives of the mutual information function I with respect to the weighting parameter vector w, the conjugate gradient (CG) algorithm is employed to derive the weighting parameter vector with maximum mutual information iteratively. Detailed derivation of the derivatives is shown in *Appendix* and interested readers may refer to [9] for more information.

3.2 Class-related histogram generation

For an RGB-formatted color image I, the entire color space can be uniformly divided into $N \times N \times N$ histogram bins. Then the high-resolution color histogram can be generated by calculating the number of pixels contained in each bin and the histogram vector can be represented as $\langle h_{111}, h_{112}, \ldots, h_{NNN} \rangle$. It is shown in Section 2 that there are inevitably lots of empty components since some particular color seldom appears in natural images. These components are apparently useless to describe the image and considering them will increase the feature dimension and computational complexity in the subsequent classification process. Hence, the empty components are first excluded from the histogram vector. In addition, some non-empty components also do not contain discriminative information for image classification. Furthermore, as there are definitely much relationship between neighbouring components (also shown in section 2), taking it into account may improve the performance. In the proposed algorithm, the neighbouring relationship is described by a linear combination of data contained in several components. It should be noted that only the relationship between adjacent components (their color distance is below a preset threshold) is approximately represented by linear correlation because the relationship among all the histogram components may not be linear and using high-order statistics to describe such non-linear relationship is very complex and computational expensive.

Based on maximization of the mutual information criterion, the class-related histogram quantization method is carried out as follows:

I. Detect and mask out empty components (the average value of a specific bin below a preset threshold, T_{Emp}, is defined as an empty component) and set the feature index i=1.

II. Calculate the discriminative power of each single feature (the MI value between the feature and the class label). Select the most discriminative feature with highest MI value (denoted by $I_{previous}$).

III. Form the candidate set by combining the component(s) with most discriminative feature and each of its (their) neighbouring component(s). Remove the groups from the candidate set whose color compactness (denoted by the maximum color distance) is greater than a preset threshold, Max_{dist}.

IV. From the candidate set, select the group of components with highest MI (denoted by $I_{current}$). If $I_{current} > I_{previous}$, combine the components in the group and update the most discriminative feature set and its MI value ($I_{previous}$) with $I_{current}$. Return to step III.

V. If $I_{current} \leq I_{previous}$, extract the ith feature and record its group components and the weighting parameter $\boldsymbol{w}_i$ which leads to the maximum MI value. Mask all the bins in the group set from further processing. If there is any component not being processed yet, increase i by 1 and go to step II. Otherwise stop.

Finally, the class-related color histogram can be generated by i) partitioning the high-resolution color histogram into several groups; ii) from each group, extracting the corresponding histogram feature vector and multiplying by $\boldsymbol{w_i}$ to generate the *i*th feature. Note that from the generation method of the new histogram feature, the former components have higher discriminative power. Hence, the new histogram feature can be further dimension-reduced by extract first several components.

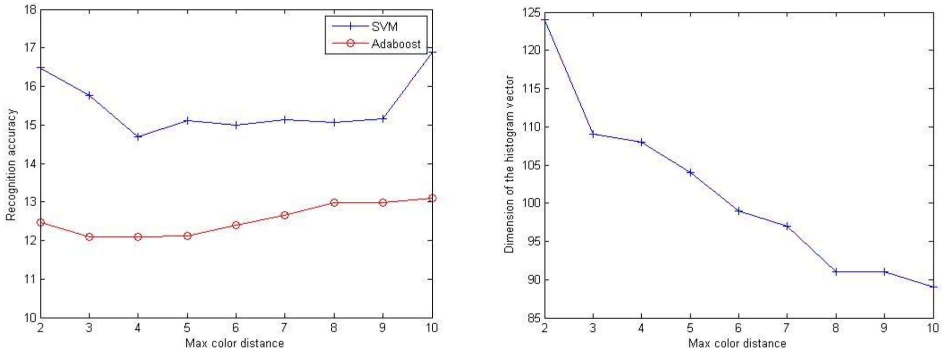
4. EXPERIMENTS AND DISCUSSIONS

To evaluate the performance of the proposed color image representation in image classification, the application of adult image detection, i.e., differentiating the nude images from the benign ones is employed. Four thousand images have been collected from the Internet to construct the image dataset for evaluation and half of them and nude images. The training image dataset for determining the quantization scheme and the corresponding weighting parameters consists of 200 nude and 200 benign images randomly selected from the entire image set. After feature extraction, two kinds of widely used classifiers, i.e., the Support Vector Machine (SVM) [10,11] and the Adaboost algorithm [12,13] are adopted for classification.

4.1 Quantization and generation of the proposed color histogram

- High resolution color histogram generation: a uniform quantized color histogram vector is described by a $10\times10\times10$ -dimension vector. To reduce the variations caused by different image size, normalization of the histogram is performed.
- Empty components masking: With T_{Emp} set as 0.0001, the bins whose average value for both nude and benign image classes are below the threshold is masked out for the subsequent processing. In our experiments, only 547 components are remained after this process which demonstrates that for natural images, their color elements do not evenly distributed in RGB color space and non-uniform quantization is more suitable for such color distribution.
- Histogram quantization and maximum color distance selection: different setting of the maximum color distance will affect the quantization result of the histogram. In order to determine an appropriate value, various settings of Max_{dist} are investigated and the recognition accuracy of SVM (in terms of the equal error rate in %) and Adaboost is taken as

evaluation criterion.



(a) (b)

Fig. 2 The recognition performance using various settings of Max_{dist}

From Fig.2, it is observed that increasing Max_{dist} helps reduce the dimension of the histogram vector because when Max_{dist} is of larger value, more adjacent color components are allowed to be categorized into one group. However, too large value of Max_{dist} also enlarges the classification error for both SVM and Adaboost. As the relationship among the adjacent components is approximated by linear combination, larger value of Max_{dist} will bring more classification error due to the omission of high-order relationship among neighbouring components. In order to evaluate the performance of the linear approximation, the average information loss ratio of the linear approximation (denoted as $\overline{R_{loss}}$) is adopted as a criterion. For each feature *i*, $R_{loss,i} = \frac{\sum_{component \in group_i} I_{component} - I_i}{\sum_{component \in group_i} I_{component}}$, where $I_{component}$ and I_i are the MI values for any color component in group *i* and the feature *i*, respectively. Then the average ratio of information loss can be computed by $\overline{R_{loss}} = \sum_i R_{loss,i} \Big/ \sum_i 1$. From Fig. 3, it is observed that $\overline{R_{loss}}$ monotonically increases with Max_{dist}, which demonstrates that too large value of Max_{dist} will induce great approximation error of the linear combination and thus degrade the classification performance.

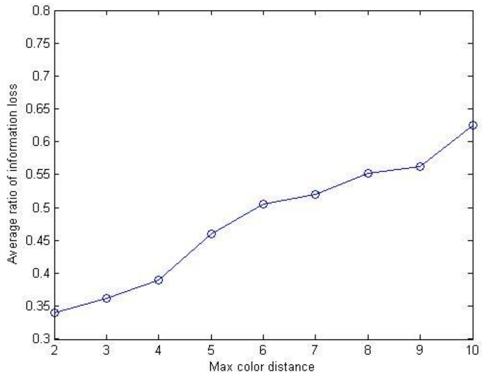


Fig.3 Average ratio of information loss caused by linear approximation with various settings of Max_{dist}

As a result, in our experiments, Max_{dist} is set to 4 for achieving the lowest EER for both SVM and Adaboost while the feature dimension is also acceptable.

4.2 Image classification results using the proposed color representation

In order to evaluate the recognition performance of the proposed color representation, two sophisticated classifiers, the support vector machine (SVM) and Adaboost algorithms are employed. SVM projects the data onto the high-dimension feature space and then performs the maximal-margin linear classification [10,11]. The incorporated kernel function helps SVM to handle many non-linear data classification. In our experiments, the Radial Basis function (RBF) kernel is adopted which produces accurate results in many image retrieval and classification algorithm in the literature. Adaboost is a recently developed iterative learning algorithm which boosts the classification performance by combining a set of weak classifiers to form a strong one [12,13]. In each iteration, the classifier will focus on the examples which are difficult to classify in the previous iterations.

To illustrate the effectiveness of the proposed color feature representation, Table.2 shows the recognition performance using the class-related color histogram (Max_{dist}=4) by SVM and Adaboost compared with the traditional high-resolution color histogram feature.

	$f_{histogram}$	$f_{class\text{-}related}$
SVM EER (%)	16.52	14.68
Adaboost EER (%)	17.27	12.09
Dimensionality	1000	108

Table. 2 Recognition performance using traditional color histogram feature and the proposed color histogram feature by SVM and Adaboost

From Table.2, it is shown that the proposed color feature representation always outperforms the traditional color histogram feature using SVM or Adaboost in both recognition accuracy and feature efficiency as well. The performance improvement using Adaboost is more significant than that of SVM. It is because the Adaboost algorithm is a combination of weak classifiers, and each weak classifier considers one single feature independently. The intrinsic connection among each neighbouring color histogram components is not much exploited in the Adaboost classifier when using the traditional color histogram. By component-grouping and linear projection, class-related information contained in such connection among adjacent components is extracted and incorporated in the proposed color representation, which greatly improves the recognition performance. For SVM, the EER by the proposed feature is also smaller than that by the traditional histogram, which demonstrates that the proposed feature representation is of more discriminative power than the traditional histogram.

Using the optimal parameter set and the Adaboost algorithm, the proposal color feature representation achieves 87.91% classification accuracy in detecting adult images. Compared with the original color histogram, over 5% accuracy improvement is achieved and the computational complexity in the recognition stage is reduced due to the lower dimensional feature vector. Fig.4 shows some false acceptance samples, i.e. benign images false-classified as erotic ones. It can be observed from the figures that the detection error may be caused by the color distributions of these images are quite similar to those of erotic images. Similar results can be observed from the false-rejection results, i.e., nude images classified as benign ones. (To avoid causing upset feeling for the readers, the false-rejection images are not shown in the paper.) Some techniques considering the spatial information (the color coherence vector [14]) and intensity texture information [15] may help improve the performance. However, such techniques inevitably require additional computation and are more time-consuming.

(a)

(b)

Fig. 4 Some false-acceptance samples

5. CONCLUSIONS

In this paper, an information-based color representation is proposed for the image classification task. Renyi's mutual information (MI) formulation is adopted to evaluate the discriminative power of each feature set. Based on the MI criterion, a new quantization scheme and feature extraction method is proposed, which takes the intrinsic relationship between adjacent color components into consideration and thus can provide a low-dimension, discriminative feature to differentiate various kinds of images. In order to evaluate the performance of our color representation, a specific image classification task of differentiating adult images from benign ones is employed. Two widely used classifiers, SVM and Adaboost, are adopted to perform classification. Experimental results demonstrate the superiority of the proposed color feature compared with the traditional high-resolution color histogram.

APPENDIX

DERIVATION OF $\frac{\partial I}{\partial \boldsymbol{w}}$

Let $\boldsymbol{x}$ be the original feature vector, y be the one-dimensional transformed feature and $y=\boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{x}$.

The partial derivative of $\frac{\partial I}{\partial \boldsymbol{w}}$ can be rewritten as,

$$\frac{\partial I}{\partial \boldsymbol{w}} = \sum_{i=1}^{N} \frac{\partial I}{\partial y_i} \cdot \frac{\partial y_i}{\partial \boldsymbol{w}} = \sum_{i=1}^{N} \frac{\partial I}{\partial y_i} \cdot \boldsymbol{x_i} \tag{A.1}$$

If y_i is in the pth class, we denote y_i as y_{pi}.

$$\frac{\partial I}{\partial y_i} = \frac{\partial I}{\partial y_{pi}} = \frac{\partial V_{IN}}{\partial y_{pi}} + \frac{\partial V_{ALL}}{\partial y_{pi}} - 2\frac{\partial V_{BTW}}{\partial y_{pi}} \tag{A.2}$$

$$\frac{\partial V_{IN}}{\partial y_{pi}} = \frac{1}{N^2\sigma^2} \sum_{k=1}^{N_p} G(y_{pk} - y_{pi}, 2\sigma^2)(y_{pk} - y_{pi}) \tag{A.3}$$

$$\frac{\partial V_{ALL}}{\partial y_{pi}} = \frac{1}{N^2\sigma^2} \left(\sum_{p=1}^{C} \left(\frac{N_p}{N} \right)^2 \right) \sum_{k=1}^{N} G(y_k - y_{pi}, 2\sigma^2)(y_k - y_{pi}) \tag{A.4}$$

$$\frac{\partial V_{BTW}}{\partial y_{pi}} = \frac{1}{N^2\sigma^2}\sum_{j=1}^{C}\frac{N_p + N_j}{2N}\sum_{k=1}^{N_j} G(y_{pk} - y_{pi}, 2\sigma^2)(y_{pk} - y_{pi}) \tag{A.5}$$

Acknowledgement

The work described in this paper is supported by the NSFC Fund (60702043) and Sponsored by Shanghai Educational Development Foundation.

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