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REGION-BASED BLOOD COLOR DETECTION AND ITS APPLICATION TO BLOODY IMAGE FILTERING

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Abstract:

Along with the widespread use of the World Wide Web, violent contents have affected our daily life. Although there are some investigations about violence video detection, few methods touch on the problem of violent and gory image detection. In this paper, we propose a region-based blood color detection algorithm. We first extract color and texture features from the detected bloody region of an image. We extract features of the whole image according to the global and local method. These features are fed into the SVM classifier. Experimental results have demonstrated the effectiveness of our proposed algorithm.

Keywords:

Blood color detection; Support vector machine (SVM); Region-based algorithms

1. Introduction

Owing to the popularity of the Internet, we can get various kinds of information brought by the Web. However, undesirable contents are also on it, such as violent and pornographic information.

These undesirable contents seriously affect the physical and mental development of netizen, particularly in children. Therefore, we must take measures to stop the spread of the undesirable information. Compared with the pornographic images, the detection of violent image is still in inadequate, in this paper we focus on the detection of violent images with full of bloody.

In recent years, many researchers have made a contribution to the detection of harmful information. Hu et al [1] propose a new algorithm for the identification of the porn information. They use the patch-based skin color detection method to recognize porn image. Lopes et al [2] use the method of establishing BOVF color histogram to detect pornographic image. Guermazi et al [3] focus on the use of colors descriptors and classifier combination to detect violent images. They proposed MPEG7 color descriptors. Wang et al [4] use the Bag-of-Words model which is frequently adopted in the image classification domain to discriminate violence images and non-violence images. They tested different feature representations in the experiments. Ulges and Stahl [5] extract the underlying image DCT features to construct the Bag-of-Words model, using the SVM to identify child pornography images. Li et al [6] recognize the horror image through the context-aware multi-instance learning method.

In this paper we use the region-based theory to detect the bloody image. Firstly, all the images are split into small blood regions as positive samples. It can satisfy us to extract color and texture features. We can use the features in SVM which is chosen as the classifier. This is a process of image segmentation to detect the blood regions, and to determine the image is violent. The second part is to examine bloody images that have the violent content. On the basis of local and global features we extract 29-dimensional features from an input image. These features are fed into the SVM classifier. The result of the experiment is promising. Therefore, our algorithm has been incorporated into a violent-content filtering infrastructure.

The remainder of this paper is organized as follows: our approach for region-based blood color detection is presented in Section 2. In Section 3, we describe its application to bloody image filtering. Finally, we conclude this paper.

2. Region-based blood color detection

Although there are some statistical blood color models, most of the existing models on blood color detection are pixel-based. In this paper, we use the region-based blood color detection algorithm for image segmentation. Some

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attributes of blood color (such as texture) are only valid in a region. We use the region-based blood color detection algorithm to extract the low level image features as it is effective. The framework of our approach is illustrated in Fig. 1.We convert the input image from RGB color space to orthogonal YCbCr color space. Y refers to the luminance component, Cb refers to the blue color component, and Cr means red chrominance component. The input image is split into small patches, and each district regional texture features are extracted based on the gray gradient co-occurrence matrix. Then we calculate the mean, variance and standard deviation of each small region in Cb and Cr color channels respectively, which generated region color features. Finally, we fuse the color and texture features together to the SVM classifier.

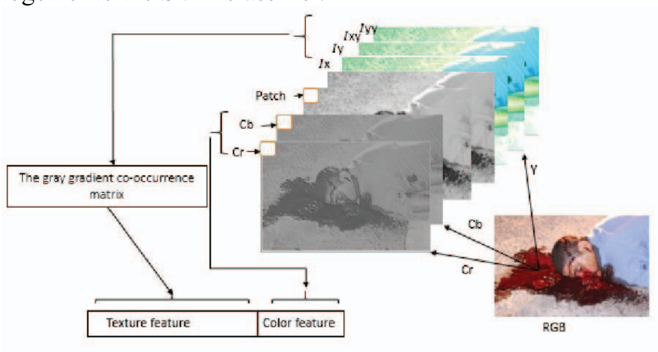

FIGURE 1. The framework of our approach

2.1. Feature extraction

We extract features from the blood color regions by sliding a window from left-to-right and from top-to-bottom. The patch size is set to 16*16 pixels. The feature generations are detailed in the following sections.

Texture feature

The gray gradient co-occurrence matrix proposed in 1973 by Haralick [7] is based on the two order conditional probability density function of an image. This method has been widely used in texture analysis.

FIGURE 2. Some sample images

Fig.2 shows some sample images which describe the difference between red things and blood tone in texture feature. The red car has a smooth and shiny surface, and the same with others. On the contrary, the blood tone is changed in different background and light conditions. Consequently, we can use this feature to exclude the pseudo blood tone.

The co-occurrence matrix is a function of distance and direction, that statistics the number of pixels in the formulary calculation window or the image pitch. For each pixel of the input image at (x, y), we assume that there is Nc pixels on the x axis, and y axis has Nr pixels. Let $Zc=(1,2,\ldots, Nc)$ for the horizontal space domain, and $Zr=(1,2,\ldots, Nr)$ for the vertical space domain. In the given direction and distance, we can get the co-occurrence matrix element $P(i, j \mid d,\theta)$ by calculate the number of the gray level co-occurrence i and j. The value of θ is usually $0°$, $90°$, $45°$, $135°$. The relationship between two pixels is illustrated in Fig. 3.

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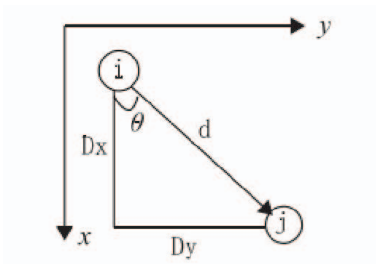

FIGURE 3. Gray level co-occurrence matrix of pixel pairs

For $d=1$, the formula of different θ to calculate $P(i, j \mid d,\theta)$ is as follows:

$A=[(k,l),(m,n)\in(Zr\times Zc)]$;

$B=f(k,l)=i, f(m,n)=j$;

$$p(i,j|1,0)=\#\left\{\begin{matrix}A\\ |k-m|=0, |l-n|=1, B\end{matrix}\right\} \quad (1)$$

$$p(i,j|1,90) = \#\left\{\begin{matrix} A \\ |k-m| = 1, |l-n| = 0, B \end{matrix}\right\} \quad (2)$$

$$p(i,j|1,45) = \#\left\{\begin{matrix} A|(k-m) = 1, (I-n) = -1 \\ |k-m| = -1, |I-n| = 1, B \end{matrix}\right\} \quad (3)$$

$$p(i,j|1,135) = \#\left\{\begin{matrix} A|(k-m) = 1, (I-n) = 1 \\ |k-m| = -1, |I-n| = -1, B \end{matrix}\right\} \quad (4)$$

Where, k, m and I, n represent the change of the selected window.

The gray level of the original image is quantized into 16 levels to accelerate the feature extraction. We get the four main feature values of the co-occurrence matrix structured in four directions:

Energy

$$f_1 = \sum_{i=0}^{L-1} \sum_{j=0}^{l-1} P_d^2\,(i,j) \quad (5)$$

Energy reflects the image uniformity and texture coarseness. If all values are equal or have little difference, then f1 small. If some of the values are large and the other are small, then f1 large. When f1 is large, coarse texture, large energy; on the other hand, fine texture, small energy.

Contrast

$$f_2 = \sum_{n=0}^{l-1} n^2 \left\{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} P_i(i,j)\right\} \quad (6)$$

The contrast reflects the definition of image and texture groove depth degree. Groove depth texture, the effect clearly, on the contrary, small contrast, shallow rills.

Relevance

$$f_3 = \frac{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} ijP_d(i,j) - \mu_1 \mu_2}{\delta^1 \delta^2} \quad (7)$$

Correlation analysis is used to measure the degree of similarity of different element in the direction of the row or column. When the matrix element values uniformly equal, the correlation value is bigger; On the contrary, if the matrix pixel values vary greatly related with small value.

Entropy

$$f_4 = -\sum_{i=0}^{L-1} j \sum_{j=0}^{L-1} P_d\,(i,j) \log P_d\,(i,j) \quad (8)$$

Entropy is a measurement of the image information, and the texture information also belongs to the image information, which is a random measure. It represents the complexity of image texture. If the image has little texture, then the gray level co-occurrence matrix is almost zero. The entropy is high for the complex texture.

Finally, we use the mean and standard deviation of these parameters as the texture feature vector components.

Color feature

The color feature is the mean and standard deviation of patches in the different color channels components respectively. Compared to RGB and HSV, YCC color space has a good distribution. As shown in Figs.4 and 5, colors in the R components or H components are gathered at both ends, but in Cb and Cr channels are different. Obviously, the obtained mean and standard deviation can be more accurate by using the YCC color space.

mean: $$\mu_1 = \frac{1}{n}\sum_{i=1}^{n} a_i \quad (9)$$

standard deviation: $$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(a_i - u_1)^2}{n-1}} \quad (10)$$

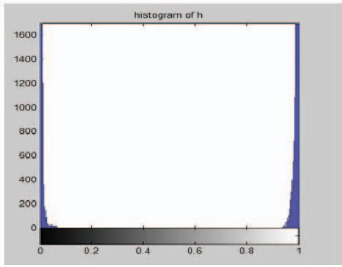

FIGURE 4. Color histogram of h

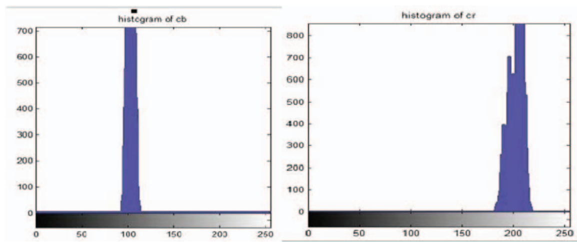

FIGURE 5. Color histogram of Cb and Cr

2.2. Classifier

The SVM classifier is selected to model blood regions as it is simple and effective. We construct two irrelevantly training sets consisting of colors and textures. Then they are passed into the SVM classifier. We get texture a model and a color model. Then we perform the test to the test set.

2.3. Dataset

We establish a new data set. Initially we collected 1000 bloody images from the violent video. And we labeled the blood region as positive sample in the database. A number of 2000 non-blood regions are used as negative samples which consist of the other scenes in the move. Moreover the red color things are also in negative samples, such as red clothes, red walls, red car etc. Although this data set may be difficult to represent all the blood tone, it can satisfy us to extracts color and texture features. Meantime, we have other 200 mixed samples in the test set.

2.4. The result of experiments

Figure 6 presents the result of our experiment with region-based method. The first row denotes the original images. The second row denotes the segmentation results of region-based. Evaluation indexes of TP (True Positive Rate) and FP (False Positive Rate) in the experiments are defined as follows:

$$TP = \frac{\text{Blood color pixel number of correct recognition}}{\text{All blood color pixels}}$$

$$FP = \frac{\text{Blood color pixel number of uncorrect recognition}}{\text{All the unblood color pixels}}$$

TP=90.8%; FP=13.2%

FIGURE 6. Color histogram of Cb and Cr

The results of Lib SVM with all features are shown in Table1. We can observe that the result is better enough to recognize the blood region.

TABLE 1. The result of Lib SVM with total features

Table Head	Parameter		
	Recall	*Precision*	F_1
Result	89.80%	91.56%	90.67%

3. Bloody image filtering

On the basis of the blood tone detection, we extract 29-dimensional blood features on each image. The features are the global image features, regional characteristics of blood and blood region shape characteristics. We use these features to construct feature vectors that are fed into the SVM classifier to detect the bloody degree of an input image. The algorithm is successful which can be applied to the bloody images filtering network. The total processes are detailed in the following sections.

3.1. Feature extraction

In this section we focus on the global and local feature extraction.

(1) Global image features

- image aspect ratio;

The aspect ratio of an image describes the proportional relationship between its width and its height. It is commonly expressed as two numbers separated by a colon, as in 16:9. For an x:y aspect ratio, no matter how big or small the image is, if the width is divided into x units of equal length and the height is measured using this same length unit, the height will be measured as y units.

- image entropy;

E = entropy(I) returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

$$E= -sum\ (p_i * log_2 (p_i))$$

proportion of blood tone region;

The blood region spatial moments;

The spatial moments of the blood region with rotation, translation, scale invariant properties. It is defined as:

$$M_{pq} = \sum_x \sum_y x^p y^q I(x, y) \qquad (11)$$

This is a (p +q) order geometric moments, and we take 0-3-order spatial moments of blood region.

$M_{00}, M_{10}, M_{01}, M_{20}, M_{11}, M_{02}, M_{30}, M_{21}, M_{12}, M_{03}$

- The number of blood region;

Local blood region features

The roundness and irregularity of the largest blood region;

The Fourier descriptor is one of the important methods in shape analysis and recognition, which has been widely applied in many fields, such as optical character recognition (OCR) [8], medical imaging [9] and industrial flaw detection [10]. To reduce the complexity of the calculation, Aragon et al. [11] defined two new indicators on the basis of roundness and irregular degree. So this paper will use the two indexes to describe the outline of the largest blood region. Roundness and irregular are defined as follows:

$$roundness = \frac{\|F_1\|^2}{\|F_{-1}\|^2} \tag{12}$$

$$irregularity = \frac{\sum_{|k|>1} \|F_k\|^2}{\sum_{|k|\neq 1} \|F_k\|^2} \tag{13}$$

where the Fourier transform can be expressed as:

$$F_n = \frac{1}{n}\sum_{k=0}^{N-1} z_k\, e^{-j\frac{2\pi nk}{N}} \tag{14}$$

- The fractal dimension of the largest blood region;

In the detection of blood image, blood regional geometry is an important feature. In the experiments, we observe that the blood region of the image presents a kind of irregular natural shape unlike the other artificial red objects (such as red wall). The fractal dimension is used to describe the irregular graphics. If the shape of the graph is similarity, then they have similar fractal dimensions. Otherwise, their fractal dimensions are different. Assume that a blood region boundary is L, regional is S, define the function Boundary (x, y) and Region (x, y) as follows:

$$\text{Boundary}(x, y) = \begin{cases} 1, & (x, y) \text{ on the boundary} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Region}(x, y) = \begin{cases} 1, & (x, y) \text{ in the region} \\ 0, & \text{otherwise} \end{cases}$$

The fractal dimension of the largest blood region can be calculated as follows:

$$D = 2\,\frac{\ln\left(\sum_{(x,y)\in L} Boundary(x, y)\right)}{\ln\left(\sum_{(x,y)\in S} Region(x, y)\right) + (\ln\alpha)^2} \tag{15}$$

- The ratio of the largest blood region area and the blood area in the whole image;
- The Hu invariant moments of the largest blood region;

After the features are extracted from violent and non-violent images, the SVM classifier is trained for classifying test images.

3.2. Dataset

Our training set contains 5000 images, including 2000 bloody images and 3000 non-bloody images. Most of the bloody images are the screenshots of violent videos. Some others mainly come from the online searching engines. Their contents are bloody scenes of all color images in JPEG format. The non-bloody images also have red car, red walls and so on. The testing set contains 500 images. We extract the features from the training set, and test them with SVM classifier.

3.3. The result of experiments

Lib SVM with RBF kernel is used with all the features. The results are shown in Table 2. We also use the pixel-based method to have some experiments, and the results are shown in table 3. Table 4 shows the comparison of different method. We can find our region-based method is really better than the pixel-based method and others. Our method can accurately detect the blood color. On the basis of this, the detection of bloody image can be more accurate.

TABLE 2. The result of region-based method

Table Head	Parameter		
	Recall	*Precision*	F_1
Result	89.86%	91.80%	90.81%

TABLE 3. The result of pixel-based method

Table Head	Parameter		
	Recall	*Precision*	F_1
Result	79.77%	83.60%	81.64%

TABLE 4. The comparison of different method

Adopted Feature	Average classification accuracy
The result of pixelbased method	83.6%
The result of BoW+LBP [4]	90.1%
The result of MPEG7 [3]	86%
The result of regionbesed method	91.8%

4. Conclusions

In this paper, we have presented a region-based blood color detection method. The experiment shows a good result for the blood color detection. We extract 29-dimensional features for its application to bloody image filtering. Finally, we test the image filter on the dataset and the result is better than other methods.

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