FACE DETECTION USING SUPPORT VECTOR DOMAIN DESCRIPTION IN COLOR IMAGES

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ABSTRACT

In this paper, we present a face detection system using the Support Vector Domain Description (SVDD) in color images. Conventional face detection algorithms require a training procedure using both face and non-face images. In the SVDD, however, we employ only face images for training. We can detect faces in color images from the radius and center pairs of SVDD. We also use Entropic Threshold for extracting the facial feature and Sliding Window for improved performance while saving the processing time. The experimental results indicate the effectiveness and efficiency of the proposed algorithm compared to the conventional PCA (Principal Component Analysis)-based methods.

1. INTRODUCTION

Over the last two decades, several different face detection techniques have been proposed and have received considerable attention due to their wide range of applications. There are some trainable algorithms for face detection, such as Neural Network (NN), Support Vector Machine (SVM), PCA, etc [1]. These algorithms have to train both face and non-face images. However, it is difficult to define a non-face image and many non-face images are required. In case of the Support Vector Domain Description (SVDD), we only need face images for training. SVDD has been inspired by SVM and it was used for novelty outlier detection by Tax and Duin [2]. SVDD algorithm can be easily extended to classification method. The basic concept is to find a sphere with a minimal radius and center, which contains most of the data. Radius and center are obtained from the support object and support vector which is the results of training the SVDD. A test data is accepted when the distance from the center is smaller than radius. When in input space, the radius alone can not represent the data and the radius is not good to classification. By using different kernels, SVDD can be made more flexible, which in turn results to more accurate classification.

Because we only use face images in SVDD, facial feature must represent the characteristic of face effectively. Therefore, we use color edges using Entropic Threshold for extracting facial feature in face candidate regions [3]. Face candidate regions are obtained in YCbCr color space and Gaussian density model [4][5]. For the improved performance of detection in various sizes of image object, we use sliding window and mask ignoring background pixels [6].

The outline of this paper is as follows. In Section 2, we review the SVDD method and show how it can be used for face detection application. In Section 3, we show the proposed system for face detection. Section 4 presents the experimental results of the proposed SVDD algorithm and a comparison with PCA. The proposed system is illustrated in Fig.1.

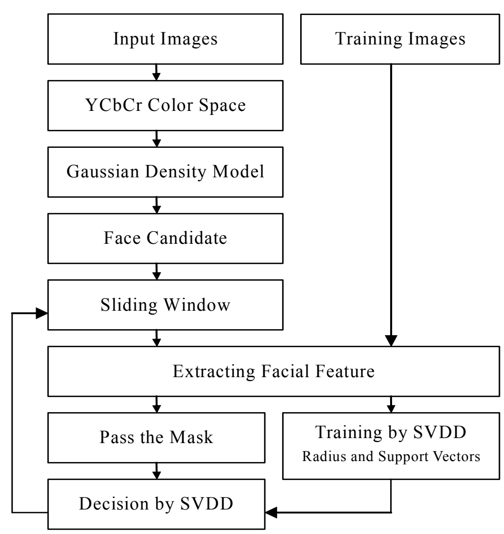


Fig.1 Face detection system

2. SUPPORT VECTOR DOMAIN DESCRIPTION

The SVDD approach is to find a sphere which contains most of data with minimal radius *R* and center *a*. Very large sphere can not represent the data very well. Therefore there are some data outside of sphere and the effect of outliers is reduced by using slack variable ξ_i.

$$F(R,a,\xi_i) = R^2 + C\sum_i \xi_i \quad (1)$$
$$where \quad \xi_i \geq 0$$

In Eq. (1), the variable C gives the trade-off between the volume of the sphere and the number of outliers. Eq. (1) has to be minimized under the inequality constraints

$$(x_i - a)^T (x_i - a) \leq R^2 + \xi_i \quad (2)$$

with the training data x_i. They form a constrained optimization problem and we can construct the Lagrangian with Lagrange multiplier $\alpha_i \geq 0$ and $\gamma_i \geq 0$ as follows.

$$L(R,a,\alpha_i,\xi_i) = R^2 + C\sum_i \xi_i - \sum_i \alpha_i \{R^2 + \xi_i - (x_i \cdot x_i - 2a\cdot x_i + a^2)\} - \sum_i \gamma_i \xi_i \quad (3)$$

The partial derivatives are equated to zero with respect to the variables and we obtain new constraints as follows:

$$\sum_i \alpha_i = 1, \quad a = \sum_i \alpha_i x_i, \quad (4)$$
$$C - \alpha_i - \gamma_i = 0 \quad \forall i$$

Since Lagrange multipliers α_i and γ_i are greater than zero, we can remove γ_i and use the constraint $0 \leq \alpha_i \leq C$.
We may rewrite Eq.(3) by substituting Eq.(4) and replacing all inner product with kernel as follows :

$$\max_{\alpha_i} L = \sum_i \alpha_i K(x_i \cdot x_i) - \sum_{i,j} \alpha_i \alpha_j K(x_i \cdot x_j) \quad (5)$$

where the constraints are $0 \leq \alpha_i \leq C$ and $\sum_i \alpha_i = 1$. Kernel satisfies Mercer's theorem. This implicitly maps the data into feature space. When a suitable kernel is chosen, a better (thus more tight) description can be obtained. A nonzero α_i is called support object while x_i is called support vector. For $C < 1/N$, no solution can be found because of the constraints $\sum \alpha_i = 1$, while for $C > 1$ one can always find solution. Therefore, when $1/N \leq C \leq 1$, C can have any influence on the solution of Eq.(5). In practice, C is not very critical. In our experiments $C = 0.2$ is chosen.

A test data z is accepted if the distance from the center is smaller than R and the decision equation is:

$$K(z\cdot z) - 2\sum_i \alpha_i K(x_i \cdot z) + \sum_{i,j} \alpha_i \alpha_j K(x_i \cdot x_j) \leq R^2 \quad (6)$$

In larger feature spaces, a Gaussian kernel, $K_G(x_i, x_j) = exp(-(x_i - x_j)^2/s^2)$, is more appropriate. Then Eq.(6) becomes :

$$-2\sum_i \alpha_i K(x_i \cdot x_i) \leq R^2 - \sum_{i,j} \alpha_i \alpha_j K(x_i \cdot x_j) - 1, \quad (7)$$

In this paper, we use Gaussian kernel. The training and test images have large vector size with the vector having 900 elements and the number of vectors is 500.

3. FACE DETECTION SYSTEM

3.1 Segmentation of face candidate regions

In Segmentation of face candidate regions in color images, selection of color model is very important. There are commonly used color model, for example RGB, HSV, YCbCr, etc. Different people have different color in appearance. Several studies show that the major difference is not due to intensity but color itself [4][5]. Thus, the image is converted into a color space containing luminance component and chrominance component like the YCbCr color model. In our experiments, YCbCr color model is used and we only consider Cb and Cr component. In our experiments, to investigate the Cb and Cr component distribution of skin color, we use 350 segmented skin images containing various human races. From the mean and covariance of Cb and Cr component, we construct the Gaussian distribution model as follows:

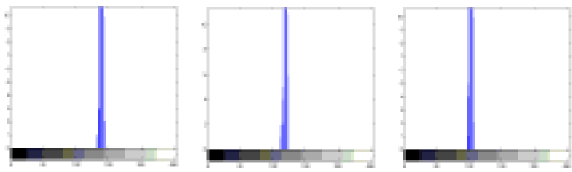
$$P(Cb,Cr) = \exp\left[-\frac{1}{2}(\mathbf{z}-\mu)^T \Sigma^{-}(\mathbf{z}-\mu)\right] \quad (8)$$
$$where \quad \mu = (\bar{Cb}, \bar{Cr})$$

In Eq.(8) $\bar{Cb}$ is mean vector of Cb component and $\bar{Cr}$ is mean vector of Cr. Also, $\mathbf{z}$ is the input pixel value. Skin region is selected by threshold, that is :

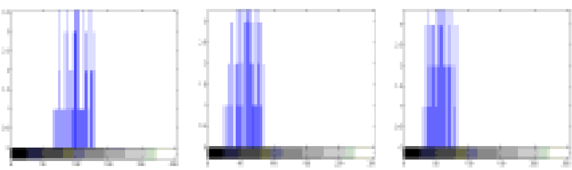
$$P(Cb(i,j),Cr(i,j)) = \begin{cases} 1, & P >= Threshold \\ 0, & otherwise \end{cases} \quad (9)$$

3.2 Facial features extraction

To extract the facial feature, such as eyes, nose and mouth in training image and test image, we use color edges. In [3], color edges are obtained by all components of YUV color space, so it spends considerable time. In our approach, we use color edges in RGB space histogram from the face candidate regions. As shown in Fig.2, the difference between skin and facial feature in Green and Blue component is more obvious than in Red component. To reduce processing time, we use Green component only.



(a) Red (b) Green (c) Blue



(d) Red (e) Green (f) Blue

Fig.2 Histogram of skin and feature: (a), (b) and (c) are histogram of skin, and (d), (e) and (f) is histogram of feature.

When we make edge image to extract the facial feature in histogram, it is most significant to decide the threshold value. We use Entropic Threshold technique for obtaining more optimal threshold. Entropy is the expectation of uncertainty. Therefore, maximum value of Entropy is the maximum point of the uncertainty. To illustrate the Entropic Threshold, let an input image intensity have range [0, M]. There are f_i pixels which have the value i, $i \in [0,M]$. Given a threshold T, the probability distribution for the edge and non-edge pixel classes can be defined, respectively. The probability for the edge pixels $P_e(i)$ and non-edge pixels $P_n(i)$ can be defined as :

$$P_e(i) = \frac{f_i}{\sum_{h=0}^{T} f_h}, \quad 0 \le i \le T \tag{10}$$

$$P_n(i) = \frac{f_i}{\sum_{h=T+1}^{M} f_h}, \quad T+1 \le i \le M \tag{11}$$

The entropies for these two pixel classes are then given as:

$$H_n(T) = -\sum_{i=0}^{T} P_n(i) \log P_n(i) \tag{12}$$

$$H_e(T) = -\sum_{i=T+1}^{N} P_e(i) \log P_e(i) \tag{13}$$

Then the optimal threshold Ť is selected by following criterion equation:

$$H(\breve{T}) = \max_{T=0,1,2,..M} [H_n(T) + H_e(T)] \tag{14}$$

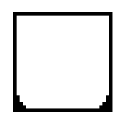
Fig.3 shows the results of color edge using Entropic Threshold method.

Fig.3 Color edge training set

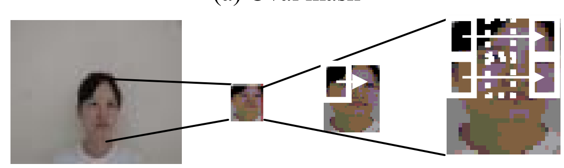
3.3 Sliding window and oval mask

Face candidate regions have various sizes in test image. When a size of face candidate region is greater or smaller than that of training image, it is difficult to find the face. Also, in order to apply the SVDD, candidate regions have to be same size as the training image. To overcome this problem, we use sliding window. In [6], a sliding widow is applied to gray image and all regions of relevant image are searched. But in color images, once a face candidate region is determined, then we do not need to search all regions. In our experiments, candidate regions are increased from 30 × 30 to 45 × 45 at 5 pixel interval. If a face can not be found in a candidate region, then the size of a candidate region is increased and a window searches the candidate region until the size is 45 × 45.

Another problem is the effect of background pixel in a candidate region. To alleviate the effect of background pixel, we use an oval mask shown in Fig.4. Using the oval make brings a better performance. Moreover we can save training and testing time by reduction of dimensionality.



(a) Oval mask



(b) Sliding window

Fig.4 Oval mask and a method of sliding window

4. EXPERIMENTAL RESULTS

In our experiments of the proposed algorithm employing SVDD, the training set has 500 frontal face images which are selected from Asian Face Image Database PF01. PF01 contains the true-color face images of 103 people, 53 men and 50 women. The detection performance is evaluated using 219 color images containing 234 frontal faces. Some parts of test images are selected from PF01, which are different from training image. Some of them were captured using digital camera and downloaded arbitrarily from various internet sites. The size of all face images is greater than 30×30.

Table.1 Detection performance

Detection Method	Correctly detected faces	False alarm	Missed faces	Detection rate(%)
SVDD	219	5	15	93.59
PCA	221	2	13	94.44

For performance comparison, we examined the performance of PCA. In PCA, we trained 500 face images (same as SVDD) and 1,500 non-face images and used the same test set. The detection performance is shown in Table 1. The detection rate of SVDD is 93.59 % and that of PCA is 94.44 %. The evaluation criterion is that if all facial parts (e.g. two eyes, nose and mouth) are not included in the detected areas, then we regard the images as a false alarm. From the results, PCA is somewhat better than the SVDD. However, the SVDD-based algorithm used only 500 face images for training with just 0.85% decrease in the detection performance. That is, we obtained similar or better performance using only face image for training. Furthermore, SVDD is more efficient in terms of processing time and dimensionality. In addition, we did not consider the non-face images. Some miss detections of SVDD are due to a wrong face candidate region by illumination condition. If we apply a preprocessing technique for luminance condition, we are likely to obtain more improved performance.

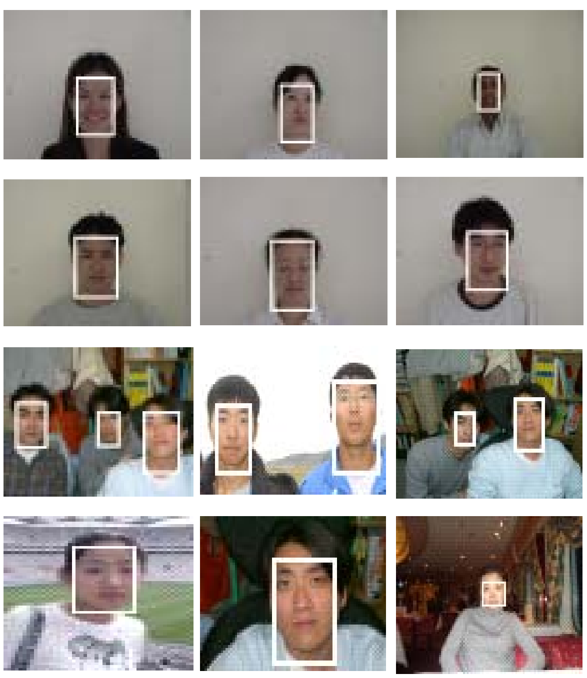


Fig.5 Result images of the SVDD

5. CONCLUSIONS

In this paper, we have proposed a face detection algorithm in color images using SVDD. In our experiments, there is no need to define non-face objects or consider the number of non-face training images. We only train with face images and obtain similar performance compared to PCA. Also in this paper, face candidate regions are extracted using Gaussian distribution model and facial feature are extracted using Entropic Threshold in color images. To increase the detection rate in various face image size, we employed sliding window and achieved superior performance.

6. Acknowledgement

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