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FACE DETECTION IN PROFILE VIEWS USING FAST DISCRETE CURVELET TRANSFORM (FDCT) AND SUPPORT VECTOR MACHINE (SVM)

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Abstract- Human face detection is an indispensable component in face processing applications, including automatic face recognition, security surveillance, facial expression recognition, and the like. This paper presents a profile face detection algorithm based on curvelet features, as curvelet transform offers good directional representation and can capture edge information in human face from different angles. First, a simple skin color segmentation scheme based on HSV (Hue – Saturation - Value) and YCgCr (luminance - green chrominance - red chrominance) color models is used to extract skin blocks. The segmentation scheme utilizes only the S and CgCr components, and is therefore luminance independent. Features extracted from three frequency bands from curvelet decomposition are used to detect face in each block. A support vector machine (SVM) classifier is trained for the classification task. In the performance test, the results showed that the proposed algorithm can detect profile faces in color images with good detection rate and low misdetection rate.

Index terms*: face detection, curvelet transform, HSV, YCgCr, SVM.*

I. Introduction

Face detection is an integral part of face processing applications, including face recognition, security surveillance, expression recognition and human computer interaction (HCI) to name a few. Given an image, the goal of face detection is to determine whether or not there are any faces in the image and, if present, return the image location and extent of each face. Face detection is challenging due to great variation in size, location, pose, orientation and expression of the human face, as well as changes of the environmental conditions (e.g. illumination, exposure and occlusion) [1].

Face detection can be broadly classified into two categories: Knowledge-based method and learning-based method. Knowledge-based method attempts to represent our prior knowledge pertaining face patterns using explicit rules such as face image intensity, elliptic face contour, and equilateral triangle relation between face and mouth [2]. However, it is not possible to translate all human knowledge exactly into the required explicit rules that could be accurately comprehended by computers. As a result, this method often performs poorly when the rule mismatches unusual faces or matches many background patches. The learning-based method tries to model the face pattern using probability distribution functions or discriminant functions. This method is not limited by the prior knowledge of face pattern but determined by the capability of learning model and training samples, hence it can handle more complex cases compared to knowledge-based method [3]. Representative examples of the learning-based method include Osuna et al.'s Support Vector Machine (SVM) method [4], Rowley et al.'s Artificial Neural Network (ANN) method [5] and Schneiderman and Kanade's Bayesian-rule method [6]. Learning-based method recorded a significant boost through the work by Viola and Jones [7], in which they proposed the use of simple rectangular features (Haar features) which can be calculated very rapidly thus reducing the overall detection time. The Haar-like features are calculated via the integral image and a cascade structure of classifiers learned by AdaBoost. Although the Haar features used in the work of Viola and Jones are very simple and effective for frontal face detection, they are less ideal for faces at arbitrary poses [8].

Skin color is an important cue for human face detection [9]. Using skin color as a cue can reduce to some extents the search space for faces and also a reduction in the number of non-face training examples. Rein-Lien Hsu et al. [9] proposed a face detection method in color images based on YCbCr color model and lighting compensation. Face detection methods using YCbCr for skin color segmentation can also be found in [10], [11] and [12]. Ghimire and Lee [13], proposed a combined YCbCr and RGB color model for skin color segmentation in their face detection algorithm. The preprocessing stage of the algorithm also involves a lighting compensation technique in HSV domain. Dios and Garcia [14] proposed another color model YCgCr for skin color segmentation. Following this work, the YCgCr color model has been used by some researchers in skin color segmentation for the face detection algorithms. Gazali et al. [15] built a Gaussian skin color model based on YCgCr and applied it for face skin color segmentation in their face detection algorithm.

Viola and Jones extended their face detection framework in [1] to address to some extents the issue of profile and rotated face [16] by building different detectors for different views of the face. A trained decision tree classifier is then used to determine the viewpoint class for a given window of the image being examined. Although this technique retains the speed advantage of the Viola-Jones detector, the reported profile face detection rate (83.1% with 700 false positives) is low looking at the number of false positives recorded. Jing and Chen [17] proposed a novel face detection method to detect faces with different poses under various environments. Skin regions are first extracted from an input and next the shoulder part is cut out by using shape information and the head part is then identified as a face candidate. A set of geometric features are used to determine if the face candidate is a profile face. These geometric features are computed from feature points like nose peak, nose bottom, nose top, and chin point that characterized a profile face. However, the test set used to assess the performance were dominated by frontal face samples and it does not suffice to attribute the overall performance to that of profile face.

In this paper, a profile face detection algorithm based on curvelet features and support vector machine (SVM) in color images is proposed. The algorithm employs a simple skin segmentation technique using HSV and YCgCr color models. In this segmentation process, only the S and CgCr components are utilized, and hence it is luminance independent. Curvelet transform is used in the feature extraction process because of its ability to capture edge information very well.

II. Curvelet Transform

Curvelet transform is a multiscale directional transform that allows an almost optimal non-adaptive sparse representation of objects with edges [18]. Curvelet transform was initially developed in the continuous domain via multiscale filtering followed by a block ridgelet transform on each bandpass image [19]. In 2006 Candes et al. [20] proposed the Fast Discrete Curvelet Transform (FDCT), defined directly using frequency partitioning without making use of the ridgelet transform. There are two implementations of the FDCT i.e. the Unequally-Spaced Fast Fourier Transform (USFFT) technique and the wrapping-based technique. Wrapping-based FDCT is faster [20] and is the technique that is employed. In this technique, given an image f (m,n) of size MxN, both the image and the curvelet function are transformed into Fourier domain. After transformation, the Fourier product between image and curvelet function is obtained. This is equivalent to applying convolution in the spatial domain. In the end, curvelet coefficients are obtained by taking the inverse Fourier of the product in the frequency domain. Because curvelet frequency response is a non-rectangular wedge, the wedge is wrapped into a rectangle before taking the Fourier inverse. Wrapping is achieved through periodic tiling of the spectrum using the wedge and the rectangular coefficients are collected in the center. Figure 1 adapted from [20] shows data wrapping initially inside parallelogram into a rectangle by periodization. $L_{1,j}$ and $L_{2,j}$ represent the height and width of the parallelogram respectively.

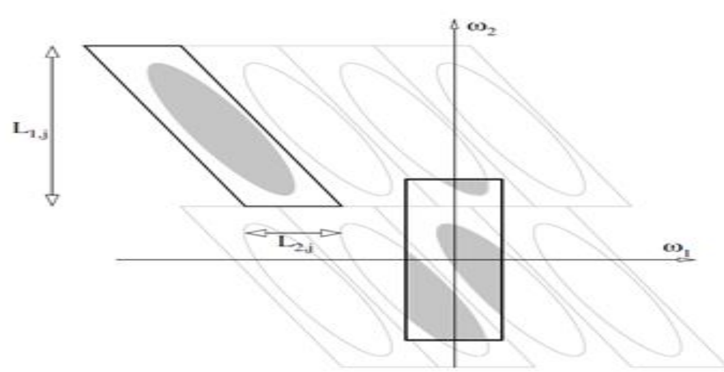

Figure 1: Data wrapping, from parallelogram into a rectangle by periodicity

The digital curvelet equation is given by [21]:

$$c^{\mathrm{D}}(a,b,\theta)=\sum_{\substack{0\le m<M\\0\le n<N}}\mathrm{f}[m,n]\varphi^{D}_{a,b,\theta}[m,n] \tag{1}$$

where:

C^{D}: Discrete curvelet coefficients

φ^{D}: Curvelet function

a: Scale parameter

b: Location parameter

θ: Orientation parameter

The advantages of using the curvelet transform include the following [18]:

- Optimal sparse representation of curve singularities (edges).
- In addition to parameters of scale and position (as in wavelet), curvelet also adds one more parameter of direction.
- Curvelets are designed to handle curves (edges) using only a small number of coefficients.

The two curvelet implementations in Matlab can be obtained from [22].

III. Face Detection

The proposed face detection algorithm takes a color (RGB) image as input. Skin detection is then applied to extract skin region(s) from the input image as the possible face candidates. The next step is the application of curvelet transformation to the skin block(s) for feature extraction. The extracted features are used to classify a given skin block, either as face or non-face, using a trained Support Vector Machine (SVM) classifier. SVM classifier has been successfully applied for other computer vision applications like vehicle classification [23], pedestrian detection [24] and many other classification tasks. Figure 2 shows the block diagram of the proposed algorithm.

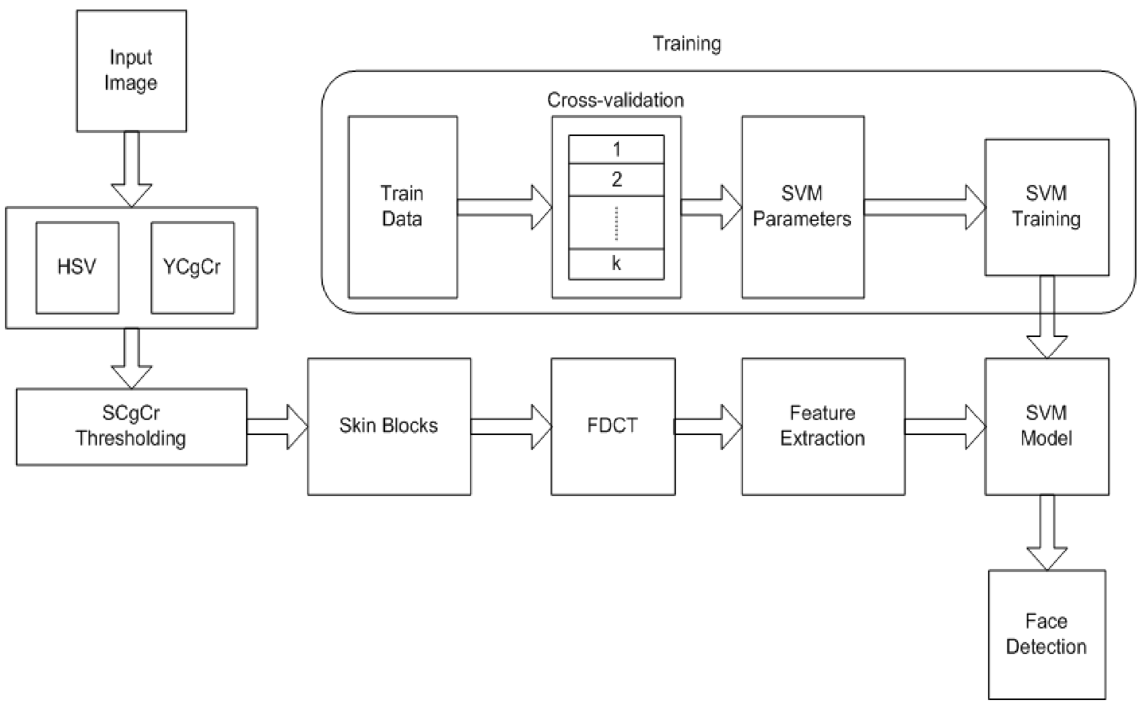

Figure 2: Block Diagram of Proposed Face Detection Algorithm

3.1 Skin Color Detection

Skin detection served as a primary stage for many image processing applications including face detection [9]–[11], [25] , finger direction detection [26] and many other related applications. A study by [27] had shown that the HSV and YCgCr color spaces scored best for skin color segmentation. Based on this, simple skin color segmentation is proposed utilizing the two color spaces. The transformation from RGB to YCgCr can be achieved using the equation [27]:

$$\left.\begin{aligned} Y &= 16 + 65.481R + 128.553G + 24.966B \\ C_g &= 128 - 81.085R + 112G - 30.915B \\ C_r &= 128 + 112R - 93.768G - 18.214B \end{aligned}\right\} \quad (2)$$

Transformation from RGB to HSV is non-linear and can directly be achieved in Matlab. After these transformations, the S and CgCr components are used to extract the skin regions. The model for determining the skin color tone in the Cg-Cr chrominance space [28] is described in the equation below:

$$\left.\begin{array}{ll} C_r \in [-C_g + 260 & -C_g + 280] \\ \mathrm{C_g} \in [\ \ 85 & 135] \end{array}\right\} \qquad (3)$$

Saturation value, S for skin color lies in the range $0.23 \le S \le 0.68$ [29]. In this work, an upper saturation bound of 0.7 is used. Figure 3 shows some skin detection results using this scheme.

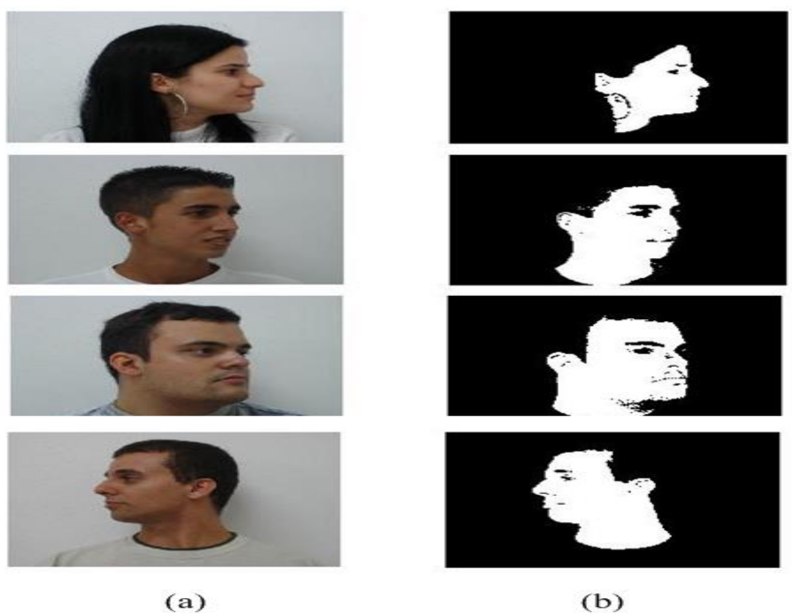

Figure 3: Skin Detection (a) Original Image (b) Segmented Image

After the segmented skin blocks are obtained, some morphological operations (i.e. erosion and dilation) are applied to remove noise and holes from the image. Small area rejection is used to remove smaller blobs that are too small to be a face.

3.2 Experimental Data

In this study, the face training samples were prepared from the FEI (part 1 and 2) dataset [30], 40 subjects were used, and each subject had 14 different instances; hence a total of 560 face training images were used. Each face image is cropped and size-normalized to [64 64]. Figure 4 shows some samples of the face training data. Non-face images were prepared from the Pratheepan database [31], FEI (part 1 and 2) database [30] and some non-face samples from [32]. Each image was size-normalized to [64 64]. In total, 450 non-face samples were used. Some extracted non-face samples are shown in Figure 5.

Figure 4: Extract from Face Training Samples

Figure 5: Extract from Non-face Training Samples

3.3 Feature Extraction and Classification

In order to extract features from the image, each image was decomposed using the Fast Discrete Curvelet Transform (FDCT) via the wrapping technique. Four scale of decomposition was used i.e. the image is resolved into four different bands:

- Approximation details
- Scale two details
- Scale three details
- Finest details

The number of angles at the second details was set to eight (8). Three scales were used to extract the features i.e. approximation, scale two and scale three details. In the second and third details (second and third scales), half of the number of sub-bands was used because a curvelet at angle θ would be the same at θ+π due to symmetry [21]. From each scale, four statistical features are extracted; geometric mean, standard deviation, third order central moment and kurtosis. Equation (4) to (7) gives the mathematical representation of these features.

$$Geometric\ mean = \left[\prod_{i=1}^{n} C_i\right]^{\frac{1}{n}} \tag{4}$$

$$\text{Standard deviation} = \left[\frac{\sum (\mathrm{C_i} - \mu)^2}{n}\right]^{\frac{1}{2}} \tag{5}$$

$$\text{Third central moment} = E(C-\mu)^3 \tag{6}$$

$$\text{Kurtosis} = \frac{E(C-\mu)^4}{\sigma^4} \tag{7}$$

where:

$i = 1,2,3,..............n$

n is the number of curvelet coefficients at a given scale

C is a 1-dimensional vector of curvelet coefficients at a given scale

E is the expected value

An SVM classifier was then trained using these features. The feature set was divided into 50% train and 50% test using 5-fold cross validation with grid search for SVM best parameters. The classifier was trained with radial basis function (rbf) kernel using the obtained parameters.

IV. Results and Discussion

Since our training data consists of one thousand and ten samples, then using a fifty-fifty composition, both the training and testing samples consists of five hundred and five samples each. The test result obtained on the testing samples is reported in Table 1.

Table 1: Test Result

Classifier Model	Test Samples	Test Accuracy
Curvelet (SVM)	505	96.04%

To test the proposed face detection method 200 profile images from FEI (part 3) were used. Three performance measures are used to assess the face detection algorithm. These are the detection rate, misdetection rate and number of false positive. Table 2 summarized the face detection results while Figure 6 depicts a bar plot showing the face detection and misdetection results.

Table 2: Face Detection Results

Method	Detected Faces	Detection Rate (DR)	Misdetection Rate (MDR)	Number of False Positive
Proposed	184	0.92	0.08	23
Viola-Jones	118	0.59	0.41	2

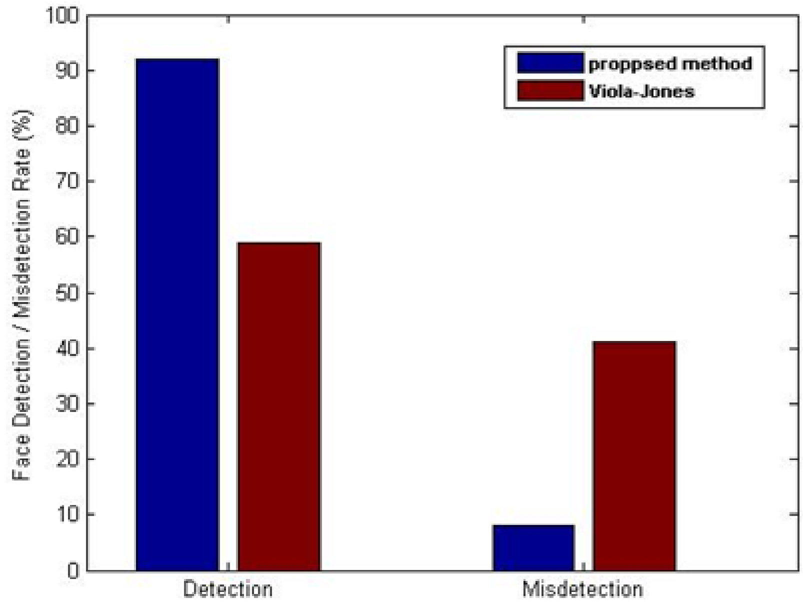

Figure 6: Bar Plot for Profile Face Detection and Misdetection

From the results in Table 2, it can be seen that the proposed method had recorded a good detection rate and significantly low misdetection rate. The number of misdetection (or false negative) is related to the recall (or sensitivity) of the classifier while the number of false positives is related to the precision of the classifier. Precision and recall are defined by the two relations below:

$$\text{Precision} = \frac{t_p}{t_p + f_p} \quad (8)$$

$$\text{Recall} = \frac{t_p}{t_p + f_n} \quad (9)$$

Where, t_p is the true positive (i.e. correct detection)

f_p is the false positive (i.e. non-face instance classified as face)

f_n is the false negative (i.e. misdetection)

For the proposed approach, the precision and recall recorded are 88.9% and 92% respectively. And for the Viola-Jones detector the precision and recall is 98% and 59% respectively. Although the Viola-Jones detector is seen to be a high precision classifier, the sensitivity (recall) is low with regards to profile faces. The proposed classifier on the other hand, shows considerably good precision and recall figures on the profile test images. However, the precision of the classifier can be improved by reducing the number of false positives. Therefore, future work will attempt to lower the false positive count of the proposed detection algorithm. Figure 7 shows some profile face detection results.

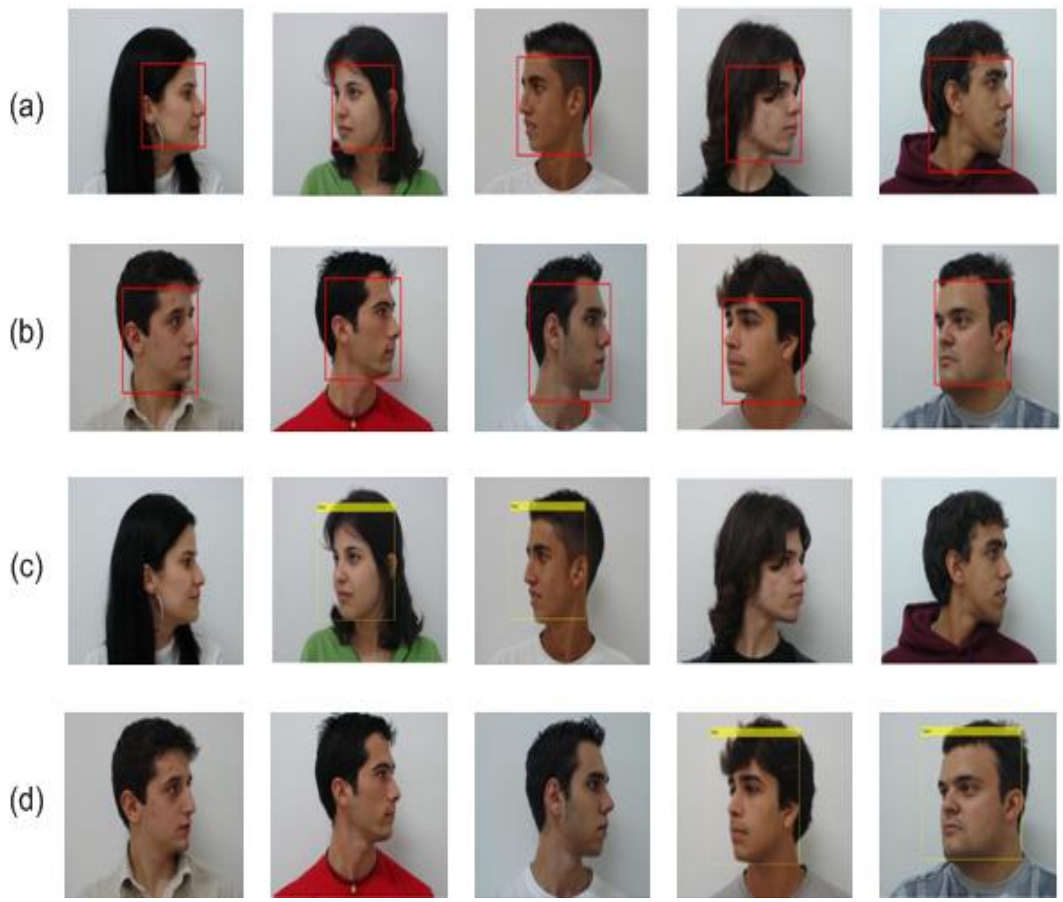

Figure 7: Some Profile Face Detection Results: (a-b) Proposed (c-d) Viola-Jones (Faces without bounding box shows misdetection)

In addition, the proposed face detection method can also detect frontal face under varying conditions including low resolution, low illumination, wearing glasses and different skin tone. Figure 8 shows face detection results on some images (under different conditions) taken from Bao face database [33].

Figure 8: Face Detection under Various Conditions: (a) low illumination (b) high illumination (c) wearing glasses (d) light skin (e-f) dark skin

V. CONCLUSION

This paper proposes a profile face detection algorithm in color images based on curvelet statistical features. Curvelet transform is a multiscale and multidirectional transform that can represent the edge information in human face very well. The main point in this research study is the use of curvelet features for face detection in profile views.

In the proposed method, a simple skin segmentation algorithm based on two color models (HSV and YCgCr) is employed. It utilizes only the S and CgCr components, and is therefore luminance independent. After the segmentation, skin blocks are generated and each block is decomposed into different frequency bands using FDCT. Features extracted from three frequency bands, excluding the finest bands, are used to detect face or otherwise in each block. A trained SVM classifier using curvelet statistical features is applied for the classification task. In the performance test, the results show that the proposed method can detect profile faces in color images with good detection rate and low misdetection rate.

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