Face Detection using Color Spatial Features and K-Means Cluster Ensemble

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ABSTRACT

In this paper a fast and robust to the changes in the detected face size method is presented. The method applies the skin color features extracted in the color spaces and a k-means clustering ensembles. There are three stages are included in the proposed method. The first, the skin-color pixel feature vector included both its position and color information is extracted. For providing fast and stable pixel classification and generating high quality region frames, a k-means clustering ensembles approach which combine the clustering results obtaining from a set of k-means clusters started from a random initialization is employed. The consensus partitions of skin color pixel feature vector can be obtained based on voting mechanism. By taking face region property into account, the optimum region boundaries are then obtained by frame integration and frame segmentation algorithms those are used for merging frames and partitioning different faces in the same region respectively. Finally, candidate face regions will be found by rejecting the framed regions when its ratio of height to width is over than 2.3. The face verification of these candidate face regions can be effectively achieved by performing an appearance-based method with spectral histograms as representation and support vector machines (SVMs) as classifiers.

Keyword: face detection, skin-color, k-means clustering ensembles, support vector machines (SVMs).

1: INTRODUCTION

Face detection is a crucial step in the face recognition system and its applications, with the purpose of localizing and extracting the face regions from the images with uncontrolled background. The task of real-time finding suitable face regions in an image with a variety of human's face size is difficulty to implement. Garcia and G. Tziritas [1] and Saad et al. [2] use skin-color classification approach to intend to simplify the face detection but the shortage occurs either that can not give compact face regions or the face regions would be missed if they are connected with the other skin-color areas like arms, human wear clothes and background. Waring and Liu [3] design a discrimination function on a fixed image window size for face detection by using spectral histograms and support vector machines. However, the face regions would also be lost if the size of these face regions are bigger or smaller over than the predefined image window. Recent works [4-7] have demonstrated that combining multiple classifiers result in reduced test set error. L. I. Kuncheva and D. P. Vetrov [8] give some experiments to evaluate the stability of k-means cluster ensembles with respect to random initialization and have conclusion that ensembles are generally more stable than individual clusterers. Rob byrd and Ranjanibalaji [9] addressed an video face detection approach by using color ratio and k-means clustering that can achieve in real time processing. However, there are generally unstable when segment the face region by one classifier. Hence, in this paper, a fast and robust to the changes in the detected face size method is presented. The method applies the skin color features extracted in the color spaces and a k-means clustering ensembles. The experiments is conducted and shows that the proposed method can not only precisely detect faces in image with a variety of face size and contaminated by the noise such as the non-face skin-color objects, arms, object's color similar to skin-color, wearing clothes and background object, and some of these faces overlapped, but also provide a more stable face detection solution.

2: COLOR MODELS FOR SKIN-COLOR CLASSIFICATION

In face detection, preprocess based on skin-color classified can effectively provide probable of face locations in color images. However, a Bayesian approach will give more effective and precision in setting skin-color distribution from ample training data to skin-color classify.

2.1: YCbCr COLOR SPACE

About YCbCr color space [11], it has been defined in response to increasing demands for digital algorithms in handling video information, and has since become a widely used model in a digital video. The luminance component Y has an excursion of 219 and an offset of +16. And the chrominance components Cb and Cr have excursions of +112 and offset of +128, producing a range from 16 to 240 inclusively. However, in YCbCr color space, the Bayes decision rule for minimum cost [12] can be used to classify sample I into skin color class (ω_1 or 1) and non-skin color class (ω_2 or 0). The Bayes decision rule for minimum cost is expressed as

$$p(I \mid \omega_1)/p(I \mid \omega_2) > T \quad \Rightarrow \quad X \in \omega_1 \tag{1}$$

$$p(I \mid \omega_1)/p(I \mid \omega_2) < T \quad \Rightarrow \quad X \in \omega_2 \tag{2}$$

and

$$p(i \mid \omega_1) = Cs_i / Ts \qquad i \in I \tag{3}$$

$$p(i \mid \omega_2) = Cn_i / Tn \qquad i \in I \tag{4}$$

where T is a threshold refers to [10]. Cs_i represents the number of skin color at position of Cb and Cr, and Ts is the total number of skin color from all samples in the color space. Correspondingly, Cn_i represents the number of non-skin color at position of Cb and Cr, and Tn is the total number of non-skin color from all samples in the color space.

In addition to classify skin-color by this Bayesian approach, there were equations already defined the bounding planes in many researches in YCbCr color space [16-17]. So, it is also a convenient for researchers to skin-color classify without consuming most of time in training skin-color map.

2.2: HSV COLOR SPACE

Beside YCbCr color space, HSV color space is also a main concern in skin-color classification. The HSV (hue, saturation, and value) model [13] is commonly used in computer graphics applications. It also known as HSB (hue, saturation, brightness) and defined a color space in terms of three constituent components. Hue is the color type, such as red, blue, or yellow, and ranges [0, 360]. Saturation is the vibrancy of the color, intensity of a specific hue. It is based on the color's purity. A highly saturated hue has a vivid, intense color, while a less saturated hue appears more muted and grey. With no saturation at all, the hue becomes a shade of grey. Value is the brightness of the color, similar as luminance component Y of the YCbCr color space.

For skin-color classification, HSV color space is also a main concern. The skin-color region in HSV color space can be searched out as above approach. Or also there are equations already defined the bounding planes in HSV color space [17-18]. The skin-color pixels, be classified in an image, is then denoted as $\{d_i\}_{i=1}^{Ts}$ for K Means Clustering Algorithm.

3: SKIN-COLOR FEATURES EXTRACTION

The feature set for a skin-color pixel is selected as $X = \{position, color\}$, where the position and the color respectively indicate as, $\{v,h\}$ and $\{\{S \times \cos H, S \times \sin H\}, \{Cb, Cr\}, Y \text{ or } V\}$. The $\{v,h\}$ subset of the feature is the vertical and horizontal coordinate component of a skin-color pixel. The $\{S \times \cos H, S \times \sin H\}$ is the Euclidian distance vector in cylinder of HSV color space. The $\{Cb, Cr\}$ components in YCbCr color space are also selected as features, due to obtain sufficiency information for classification. The feature vector composed by seven components $\{\{v,h\}, \{S \times \cos H, S \times \sin H\}, \{Cb, Cr\}, Y\}$ is selected to represent the property of a skin-color pixel in a skin-color image. For getting higher speed in the feature classified algorithm and reduce noise, it is necessary to preprocess the size of original image, $M \times N$, by downsizing uniformly with a block 8×8 then the resulted image size become to $M/8 \times N/8$. The feature vector for a skin-color pixel in this resulted image must be recalculated. Setting a threshold value τ_1 for deciding each block whether it is a skin-color or not when a block downsize into a pixel? Let bn denote the number of all blocks and the amount of skin-color pixels in m 'th block as bs_m. Then the feature vector for a downsized skin-color pixel, 8×8 block in original skin-color image, can be recalculated by the following process:

Skin-color Features Extraction

Begin

  $j = 0$;

  For $m = 1$ to bn

    If ($count(bs_m) > \tau_1$)

    {

      $j = j + 1$;

      $x_j = \{\{v, h \mid \text{the center position in } m\text{'th block}\},$

        $\{\{E[S \times \cos H], E[S \times \sin H]\},$

        $\{E[Cb], E[Cr]\},$

        $E[Y \text{ or } V]\} \in bs_m\}$;

    }

    $n = j$;

End

4: THE ADAPTIVE FACE DETECTION METHOD

The adaptive face detection approach that consists of feature classification algorithm, frame integration algorithm and frame segmentation algorithm is developed to effectively detect the candidate face regions in an image with variety of human's faces and counteract noise.

For improving both the robustness as well as the stability of unsupervised classification results, many researchers have recently interested in the cluster ensembles. An ensemble of classifiers can be regarded as a set of classifiers that each of decisions are combined in some method, archetypical by weighted or un-weighted voting to classify. An ensemble method by un-weighted approach is employed in our paper that attempt to find a both efficiency and effective face detection method based on k-means algorithm.

4.1: K-MEANS CLUSTER ENSEMBLES ALGORITHM FOR SKIN-COLOR PIXELS

The k-means clustering is an algorithm to classify object based on features or attributes into k number of group. The group is done by minimizing the sum of squares of distance likely Euclidean Distance between data and the corresponding cluster centroid. But the results of this classification algorithm are sensitive to the initialized randomly cluster centroid. Hence a k-means clustering ensemble composed by a set of k-means classifier is consulted. The basic framework for cluster ensembles is shown Fig. 1

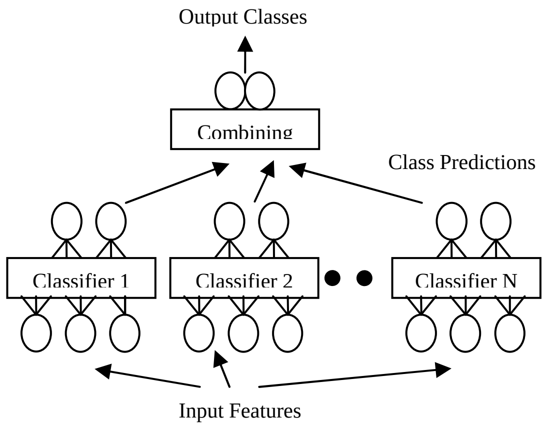


Fig. 1 Basic framework for cluster ensembles

There is a shortage in performing k-means classifier. That is, this classifier force all the feature points to must be classified into a cluster one of a certain number of clusters fixed a priori. If there are noises, the partition regions will be enlarge and result in mistake. Hence after performed clustering, the partitions are refined to discard the skin-color pixel which is far away from cluster centroid in the cluster as its distance from the cluster centroid is two larger than the pixel position variance of the cluster. In Fig. 2 shows an experimental result some region areas are larger the skin-color areas. The phenomenon occurs when noises exist. Partitions are processed to eliminate the singularity points. Experimental result shown in Fig. 2 demonstrates that the regions size is more close to skin-color area.

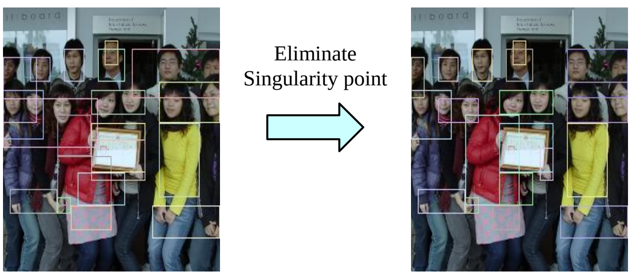


Fig .2 A sample test by Eliminate Singularity point

The major steps for forming the k-means clustering ensembles algorithm are described by the following:

k-means Clustering Ensembles Algorithm

Inputs: The results of each k-means classifier, k-means clustering to be run from initialized randomly centorid.

Output: Label the partitions and determine the members of each labeled cluster by counting the number of each of all the features that occur in the certain labeled cluster.

Procedures:

Begin

For i=1 to Q

Q is the number of classifier combined into a clustering ensemble.

run steps of the i'th k-means classifier

step 1: assignment **:** Assign the cluster number of K**.**

step 2: Initialization**:** Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.

step 3: distance measurement: Assign each object to the group that has the closest centroid use Euclidean distance. When all objects have been assigned, recalculate the positions of the K centroids.

step 4: termination**:** Repeat Steps 2 and 3 until the centroids no longer move.

obtain a set of partition C_{ij} the jth partition of the ith k-means classifier, j=1,….., K, K is a number of clusters fixed a priori

End

Cluster labeling: Determine who is who according to the condition of the same partition in different classifier almost has same members in C, $C = \lfloor C_{ij} \rfloor_{Q \times K}$. And then the partition is ordered and labeled by the occurrence number of the partition, the larger the number the more stability of the partition.

Member Determination: Assign the feature point as the members of a labeled cluster due to the feature point have most occurrence number in the cluster.

End

Using k-means clustering ensemble for face detection, the skin-color pixels are classified by applying the extracted pixel feature vectors to a k-means clustering ensembles method to find skin-color regions frame. Before implementing clustering, the features must be respectively standardized because the essence and measured units of these variances are diverse to mutually comparison. Let x_j denote the j'th skin-color pixel feature:

$$x_j = \{v_j, h_j, (S\times\cos H)_j, (S\times\sin H)_j, Cb_j, Cr_j, Y_j\}, \quad (5)$$

and x_{jk} represents the k' th element of the j' th feature vector and the standardized feature elements x_{jk}^s are noted as:

$$x_{jk}^s = (x_{jk} - \bar{x}_k)/\sigma_k \quad \forall j = 1,\cdots,n \text{ and } k = 1,\cdots,7. \quad (6)$$

where $\bar{x}_k$ and σ_k are the mean and the standard deviation of k' th element, and n is represents the total number of clustering skin-color pixels.

After standardization, there are five elements in the color components, those contain $\{S\times\cos H\}$, $\{S\times\sin H\}$, $\{Cb\}$, $\{Cr\}$, and $\{Y\}$ and each of them is respectively standardized to 1 unit. In the position components, only two elements $\{v\}$ and $\{h\}$ are standardized to one unit respectively. Thus the total quantities of color and position elements are not equal. Owing to balance the influence between both position and color component, we have to adjust position element value as follow:

$$y_j^t = \{2.5\times\{v_j, h_j\}^s, (S\times\cos H)_j^s, (S\times\sin H)_j^s, Cb_j^s, Cr_j^s, Y_j^s\} \quad (7)$$

In order to facility the representation of the features vector, y_j will be redenoted as

$$y_j = \{v_j'^s, h_j'^s, (S\times\cos H)_j^s, (S\times\sin H)_j^s, Cb_j^s, Cr_j^s, Y_j^s\}^T$$
$$v' = 2.5v;\ h' = 2.5h, \quad \forall j = 1,\cdots,n. \quad (8)$$

When the extracted skin-color pixel feature vector normalized, a k-means clustering ensemble method with un-weighted approach is applied to effectively classify skin-color pixel features and find out regions frame in an image. All face could be roughly framed and the performance was shown by a sample result as Fig. 3. And in order to get the better result, the optimum of framed boundaries, candidate face regions would be further treated by follow algorithms.

4.3: FRAME INTERGRATION ALGORITHM FOR MERGING REGIONS

After performance by clustering algorithm, many of faces in image were precisely framed for fit regions, but there is an exception if the factual face area was bigger to a certain extent. It would cause the factual face area to be multi-framed at the same face because the location was a main distance about clustering element. A sample result is shown in Fig. 4 (a). Hence, we simply propose a frame integration algorithm for regions union if these regions belong to the same face. The values of initial setting are our experience from a variety of images. Fig. 4 (b) shows the sample result after the frame integration algorithm.

Frame Integration Algorithm

Initial: Set $\tau_2 = 1/2$, $\tau_3 = 1/5$, $\varsigma_1 = 1.5$ for follow decision rules;

Rule 1: Exists area overlap between adjacency frames.

Rule 2: Number of skin pixels in each framed should be greater than τ_2.

Rule 3: The length of the edge of the overlapped are of the two overlapped frames must larger than τ_3.

Rule 4: If the above rules satisfied, the crucial rule which according to the statistic of empirical rule based on bell shaped, Fig. 3.5, is mainly aimed at deviation of color relation, sets of $\{Y\}$, $\{Cb\}$, $\{Cr\}$, $\{S\times\cos H\}$, and $\{S\times\sin H\}$. First, concerning about brightness set $\{Y\}$ between F_a and F_b, the mean and standard deviation of F_a and F_b must be computed, respectively denote as μ_{ya}, σ_{ya} and μ_{yb}. About F_a, value of μ_{yb} should be limited between $\mu_{ya} \pm \varsigma_1 \cdot \sigma_{ya}$.

And then the other restrictions in color sets of $\{Cb\}$, $\{Cr\}$, $\{S\times\cos H\}$ and $\{S\times\sin H\}$ are same as above, $\{Y\}$.

Rule 5: If through all rules above were accepted, we can use a union list to record $F_a \leftarrow F_b$, which represent $F_b \in F_a$.

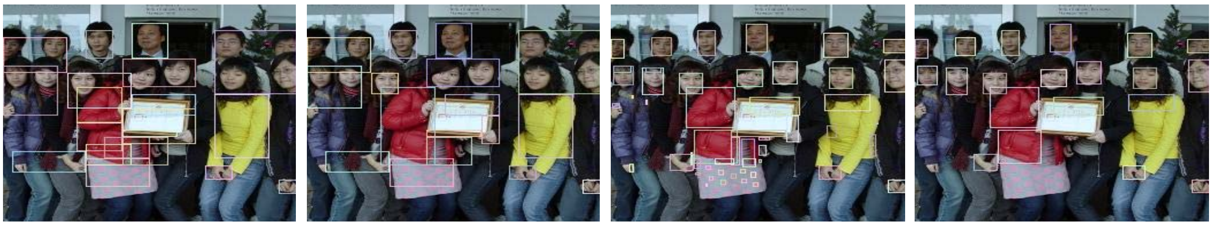
Rule 6: Combining regions according to the union list.

4.3: FRAME SEGMENTATION ALGORITHM

By way of the frame integration algorithm, most of the regions which belong to the same face would be effectively united. Then, in this section, there is an algorithm which is used to frame segmentation with candidate face regions, that maybe there are faces in a same frame caused by step of clustered or integrated approach, to give an optimum of boundaries. The analysis in this algorithm, describes as follows, mainly by the bitmap and a sample result is shown in Fig. 3 (c).

(a) (b) (c) (d)

Fig 3. A sample test by a k-means clustering algorithm. (a) The original image; (b) The skin color image based on union of YCbCr and HSV color spaces; (c) The Bitmap; (d) Result after the algorithm.



(a) (b) (c) (d)

Fig 4. A sample test for candidate face regions. (a) The result by clustering algorithm; (b) The performance after frame integration algorithm; (c) Processing by frame segmentation algorithm; (d) The final result after forsaking the unlikely regions.

Frame Segmentation Algorithm

Preprocess: Generally, there were many non-skin color pixels (as eyes, eyebrows, nose, mouth, and too light or dark location) in the face region. These would make to partition of actual face region into independent framed areas by frame segmentation rules follow. Hence, we suggest a simple method to fill up these pieces of non-skin color pixels. For main of horizontal fractions, we can use a column mask (5×1 pixels in our experiment) to filter with the bitmap. In filtering, the step first is to search position of both upper and lower pixels, which are belong to ω_1 denote as p_1 and p_2. Then, the second step is setting ω_1 for pixels between p_1 and p_2. In the same way, for main of vertical fractions, we can use a row mask to filter with the bitmap. And then to iterate until the bitmap is no changed, the performance of a sample result is shown in Fig. 5.

Step 1: About vertical segmentation, in order to get a threshold of suitable value in each framed region, we also use a statistic of empirical rule, which is mainly aimed at deviation about each number of skin-color pixels of column in a framed region by the bitmap. So, the step first is to compute the mean and standard deviation, respectively denote as $\mu_v^{(R_a)}$ and $\sigma_v^{(R_a)}$, by each number of skin-color pixels of column $col_i^{(R_a)}$ in a'th framed region R_a. However, a notion is not to underestimate for $\sigma_v^{(R_a)}$, let set

$$\sigma_v^{(R_a)} = \left\{\sum_{i=1}^{l_v}(col_i-\mu_v)^2 \Big/ (l_v-1)\right\}^{1/2} \tag{14}$$

and $l_v^{(R_a)}$ is the length of row pixels in the framed region.

Then, the threshold of suitable value $\tau_v^{(R_a)}$ is given by

$$\tau_v^{(R_a)} = \mu_v^{(R_a)} - \sigma_v^{(R_a)} . \tag{15}$$

Step 2: To consider that if $\tau_v^{(R_a)}$ becomes a smaller or greater of unreasonable value. About segmentation, the framed regions would be bound to segment when any $col_i^{(R_a)}$ is equal to zero. And the framed regions would not be segmented if $col_i^{(R_a)}$ is greater enough. Therefore, let set

$$\tau_v^{(R_a)} = \max(\tau_v^{(R_a)},1) \tag{16}$$

and

$$\tau_v^{(R_a)} = \min(\tau_v^{(R_a)},\varsigma_2\cdot l_v) , \tag{17}$$

where ς_2 is a fraction by l_v (our experiment set $\varsigma_2 = 1/3$).

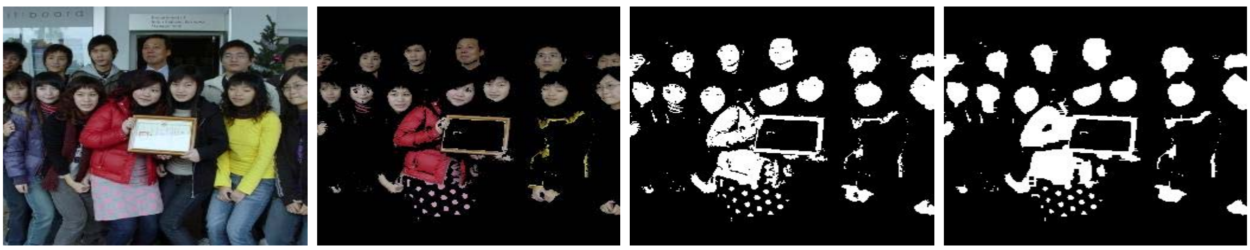
Step 3: The framed region $\{R_a\}_{a=1}^{c^*}$, where c^* is the number of framed regions, would be segmented if position of $col_i^{(R_a)}$ smaller than $\tau_v^{(R_a)}$. Equally, we can use the same steps above for horizontal segmentation.

Step 4: Iterating between steps 1 and 3 until all framed regions are non-alteration. The optimum of candidate face regions will be found as Fig. 4 (c).

4.4: UNLIKELY FACE REGIONS DETECTION

After algorithms above for detecting of candidate face regions, the final process is to forsake unlikely regions, similar as smaller area or a wide gap about the ratio of height to width over than 2.3 to 1. A sample result is shown in Fig. 4 (d).

5: EXPERIMENTAL RESULTS



(a) (b) (c) (d)

Fig 5 A sample result by preprocess of frame segmentation algorithm . (a) The original image; (b) The skin-color image based on union of YCbCr and HSV color spaces; (c) The Bitmap from original image;

Generally, some time color light due to the departure of color of testing images. So to get more efficient results of face detection, in our experiment, we can eliminate the disturbance of color lights by "color balance suppose" [18-19] before we detect skin-color pixels use skin color classification algorithms.

The performance of the proposed method has demonstrated in Fig.4. The size of these testing images is 256×256 pixels. After processing by algorithms above, about forsaking the unlikely regions, we only use some threshold rules based on shape, similar as too small area or a wide gap about the ratio of width and height, in our experiment. But there was a fundamental relationship [22] between the number of connected object components and the number of object holes in a candidate face region called the Euler number, defined by [25], could be use to reject some survival of regions. Due to a skin region is defined as a closed region in a candidate face region, which can have at least one hole, represent eye, mouth, or etc., inside it because they are not skin-color pixels. They appear as holes inside the region, but other skin regions such as arms or legs have no holes inside them. So if the candidate face region with no holes, it also can be rejected.

Finally, recognition of the face regions in a color image is performed by an appearance-based method using spectral histograms as representation and support vector machines (SVMs) as classifiers [23].

6: CONCLUSTION AND DISCUSSION

We have used a k-means clustering ensemble combined a set of un-weighted k-means classifier for segmenting the face region in the image. The experimental results have demonstrated that the proposed method can achieve both the robustness and the stability in face detection. And also get the efficiency advantage of k-means algorithm in classification problem. However there is an inherent drawback that the number of cluster must be fixed a priori. The drawback could reduce the application. In the paper we give the cluster number for k-means classifier twenty clusters for more faces and ten clusters for less faces in an image. The performance compared to the SCM approach [26] have almost same face segmentation results, but obtain the larger reduction of computational time.

By our proposed adaptive face detection method in this paper, the suitable size of facial regions will be effectively detected in images even if the images contain skin-color objects that are not human faces, such as hands and background object, or any object near faces or these faces are overlap. Therefore, we can use one of many decision methods to detect human's face. However, most captured faces are usually distorted by a linear transformation, which typically includes scaling, rotation, shearing, and translation transformations of an object called affine transform. The affine distorted will critically affect most of decision methods. Thus, we can use some robust method [20-22] to make restored for these distorted faces. Moreover, a reliable method [23] using spectral histograms [24] and support machines (SVMs) in this paper can provide an accurate detection without considering affine distorted.

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