Chapter 2

Multivariate Histogram Based Facial Feature Segmentation and Classification

Facial feature extraction is one of the important requirement of many face detection and recognition techniques. Segmenting the facial features from the facial regions is the aim of this chapter. Univariate histogram thresholding is one of the commonly used techniques for segmentation of pixels in gray images. For color images, to get control on color bands and emphasizing on color information for clustering, the multivariate histograms are effective. In this chapter, the 2D and 3D histograms are used for clustering the pixels to extract the facial features as major segments. The RGB color bands along with the infrared(IR) band information are used to form the multivariate histogram.

A portion in this chapter is from the paper [117] of the author.
This chapter consists of four sections. After a brief introduction in section 2.1, section 2.2 deals with the construction of multivariate histogram. The concepts of valley regions are also briefly described in this section. In subsection 2.2.1, a modified graph theoretic algorithm is presented which performs the segmentation. Two sets of experiments are designed. The first one shows the application of the proposed method on an artificial data, and the second one shows the application on face dataset. The technique is supported by test results.

2.1 Introduction

Facial feature extraction is considered as a preprocessing stage in many face related applications. Though in general, facial features are used for face detection [22], yet there are some applications of using segmented facial features in face recognition [23]. During the last 20 years, numerous facial feature extraction algorithms have been proposed [24],[126]. However, finding dominant facial features, invariant to rotation, scaling, translation and viewing angle still remains a challenging problem.

The techniques of feature extraction are mostly based on skin color segmentation [127],[26],[27],[28], deformable models [29], neural networks [30], and geometrical models [31]. The feature based methods [24],[27],[28] combined with geometrical facial templates are found to be useful for face detections in both frontal and non profile views [33].

With the availability of color digital image databases, the development of efficient segmentation methods using color channels are attempted [34],[128].
Additionally, thermal (IR) imagery is also a source of information for detection and recognition of faces [35], [36], [129]. Thermal cameras can sense temperature variations in the face from a distance and produce thermogram in the form of 2D images. Face recognition in the thermal (IR) offers some additional advantages [130], [131] since IR images are illumination invariant and therefore the intra class differences are significantly lower than that observed in visible imagery. In this chapter the IR images are used as an additional channel for segmentation over and above the RGB channels.

Feature extraction is governed by several segmentation algorithms for the color images namely clustering methods, histogram based region growing methods [132], etc. Some works are reported [133] on finding peaks and valleys in bivariate and multivariate histograms. The early work in this area was related to the development of an algorithm involving parent-child relationship between bins in a bivariate histogram [134]. The number of clusters in the method depends on the choice of control parameters. Subsequently, few other works were reported later on [135].

The basic philosophy behind the methods is guided by the observations from a single class/region which tends to form a cluster in the feature space i.e., a peak in the multi-dimensional histogram. Then the analysis is conducted to identify suitable boundaries of these peaks. The works by Goldberg and Shlien [136], Thomas et al. [133], Khotanzad and Bouarfa [137], and Majumder et al. [135] are examples of such methods. However, implicit in the peak search is the knowledge of the number of segments. Hence it is necessary to search the number of peaks in the histogram. The peak detection method considered in this chapter is basically
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guided by the algorithm described in Knootz et.al [134] and [137]. However, some pre and post processing of the data are incorporated to obtain the clusters. Later on these clusters are used for facial feature extraction, dimensionality reduction and classification [70], [89], [138].

2.2 Multivariate histogram based image segmentation

A bivariate histogram provides a histogram corresponding to two variables and hence the bivariate histogram is a matrix. If we represent the matrix as $A$ and the $(i,j)$ th element of the matrix as $a(i,j)$, then $a(i,j)$ denotes the number of pixels in the image having the gray-value $i$ for the first variable and the gray value $j$ for the second variable. The input for finding a multivariate histogram as considered here, consists of images for three color channels R, G and B and four channels R, G, B and IR for thermal imagery corresponding to the same person and taken at the same time and of the same size $M \times N$. Note that, in case of thermal imagery, we can have $4{\binom{4}{2}}$ bivariate histograms, corresponding to the band pairs (R,G), (R,B), (R,IR), (G,B), (G,IR) and (B,IR).

A trivariate histogram is represented as $H$ and each element of it is represented as $h(i,j,k)$, where $h(i,j,k)$ denotes the number of pixels in the image having gray-value $i$ for the first variable, gray value $j$ for the second variable and gray-value $k$ for the third variable. For thermal imagery, one can construct $4^{3}$-trivariate histograms, corresponding to the band triplets (R,G,B), (R,G,IR), (R,B,IR) and (G,B,IR). Any multivariate histogram can be defined similarly by
a single 4-variate histogram including a thermal image. On the other hand, there are 4-univariate histograms corresponding to the four variables for thermal imagery.

Significance of peaks and valleys of histograms are related in the formation of segments. Similar to the analysis of univariate histograms, number of peaks or the modes in a multivariate histogram signifies the number of clusters. The formed clusters in a multivariate histogram are basically the color clusters. However, there may also be spurious peaks, which needs to be eliminated. Valleys also play an important role in histogram thresholding and decides the cluster boundary. For one dimensional histogram, the valley point separates two modes. For a bivariate histogram, a valley is a line (or curve) separating the cluster regions. In case of a trivariate histogram, a valley is a plane separating two clusters.

2.2.1 Method for finding major clusters from a multivariate histogram

For the sake of convenience, the method of segmentation for a trivariate histogram is described. This can, however, be easily extended to any number of variables. The complete method of segmentation for an input image is discussed using the following algorithmic steps:

**Input**: Let the given image be represented by $I$ and the color vector of the $(i,j)$th pixel be represented by $I(i,j)$. The corresponding three variables are $R$, $G$ and $B$. Let also $min_I$ and $max_I$ denote the minimum and maximum gray values of $l$, where $l = R$ or $G$ or $B$. Let $R(i,j)$, $G(i,j)$ and $B(i,j)$ denote the color
intensity values of \((i,j)\)th pixel for the colors R, G and B respectively. Thus, 
\(I(i,j) = (R(i,j), G(i,j), B(i,j))\). The corresponding histogram be denoted by 
\(H\), and \(h(p,q,r)\) denote the number of pixels having the R value as \(p\), G value 
as \(q\) and B value as \(r\). Note that \(\min_R \leq p \leq \max_R\), \(\min_G \leq q \leq \max_G\), and 
\(\min_B \leq r \leq \max_B\).

The steps are (a) Smoothing of the multivariate histogram, followed by (b) finding the peaks and valleys and then (c) detection of the major clusters in the histogram.

**Step 1: Multivariate histogram smoothing**

A smoothing methodology for the removal of local variations in histogram is used. Let, after smoothing, the new smoothed histogram be represented by \(H_i\), and \(h_1(p,q,r)\) denotes the value of \((p,q,r)\) in \(H_1\). Then,

\[
h_1(p,q,r) = \frac{1}{27} \sum_{k=r-1}^{r+1} \sum_{j=q-1}^{q+1} \sum_{i=p-1}^{p+1} h(i,j,k)
\]

For every \((i,j,k)\) of \(H\), the above operation needs to be performed. If the maximum and minimum values are the \(f_{\text{max}}\) and the \(f_{\text{min}}\) then for each dimension, the smoothing operation needs to be performed from \(f_{\text{min}}\) to \(f_{\text{max}}\). Note that, when \(p = \min_R\) or \(\max_R\), \(h_1(p,q,r) = h(p,q,r)\). Same convention will hold when \(q = \min_G\) or \(\max_G\) or \(r = \min_B\) or \(\max_B\).

**Step 2: Finding peaks and valleys of the histogram**

Once the smoothing operation is accomplished, the smoothed multivariate histogram is used to find peaks and valleys. The process generates the tree
structure by examining neighbors of each bin and then the largest bin, i.e. the bin with the largest number of elements is selected. Then the links are established. If the current bin has the same value as the largest neighbor, one of them is selected as the father and the link is established. If the current bin is the largest among its neighbors, then the search is stopped for the current bin. Each histogram bin is connected to a bin that has the largest value in its neighborhood. Each bin is connected to a single parent bin by a path.

**Step 3: Detection of major clusters in the histogram**

A post processing step is developed to detect the major clusters in the histogram. The number of bins in every cluster is counted. The two clusters having the two largest number of bins are considered. If the number of determined peaks in the histogram is equal to or less than the desired number of segments, $K$, the algorithm is terminated. Otherwise some of the local peaks are eliminated iteratively until their number reduces to $K$. To facilitate this process, each peak is attributed with the value of the sum of its children while the child bins are set to zero. After performing the post processing, the segmented image is created.

### 2.3 Experiments and analysis of results

The proposed technique is verified by the experiments on segmenting images using histograms on an artificial as well as on real life datasets. It may be noted that the verification of the results on artificial datasets can be easily done since the model, the number of clusters and the constituent bins of a cluster are known. Verification of results on a real life image datasets is provided here quantitatively.
The obtained results on real life face datasets are subjected to classification after processing and the classification accuracy is found to improve when the segmented face regions are used for classification.

2.3.1 Verification of the algorithm on an artificial dataset

The procedure for generation of an artificial dataset is described in the following subsection. Test results by applying the proposed method on the generated artificial dataset is also analysed.

2.3.1.1 Generation of the artificial dataset

An artificial dataset with two modes is created. This dataset is generated randomly from a mixture distribution. Let the mixture density function is denoted by $f$.

$$
\text{Let, } p_1(x) = 4x; 0 \leq x < 0.5 \\
= 4(1-x); 0.5 \leq x \leq 1 \\
= 0 \text{ otherwise}
$$

$$
\text{and } p_2(x) = 4(x-1.1); 1.1 \leq x < 1.6 \\
= 4(2.1-x); 1.6 \leq x \leq 2.1 \\
= 0, \text{ otherwise}
$$
Let \( f_1(x, y) = p_1(x)p_1(y) \) and \( f_2(x, y) = p_1(y)p_2(x) \)

and let,

\[
f(x, y) = \frac{f_1(x, y) + f_2(x, y)}{2}
\]

1000 points are generated randomly from the mixture density function \( f \). There are two distinct classes \([0, 1] \times [0, 1], \ [1.1, 2.1] \times [0, 1]\) in the data set. There are two modes at \((0.5, 0.5)\) and \((1.6, 0.5)\). Each feature of each class follows a triangular distribution. 1000 points are generated from those two classes with prior probabilities of 0.5 each. After the generation of points, for each of \( x \) and \( y \) axes, class intervals of the length 0.1 are considered for forming bivariate histogram.

The number of class intervals for \( x \) values is 22 and they are \([-0.05, 0.05], \ (0.05, 0.15], \ (0.15, 0.25], \ldots, (0.95, 1.05], \ (1.05, 1.15], \ (1.15, 1.25], \ldots, \) and \((2.05, 2.15]\). The number of class intervals for \( y \) values is 11 and they are \([-0.05, 0.05], \ (0.05, 0.15], \ (0.15, 0.25], \ldots, \) and \((0.95, 1.05]\). Frequencies of each bin in 2D are also found.

Note that the variable can't take any value in the interval \((1, 1.1)\) for any class. Thus, the boundary between classes 1 and 2 will lie in the interval \((1, 1.1)\) for the variable. The proposed method provides the boundary between the classes in that interval for validation of the results.

The process of creation of artificial datasets is described below in the form of an algorithm.

**Step 1:** Generate an 11 digit random number \([0,1]\) as \(0.a_1a_2a_3\ldots, a_{11}\).
Step 2: Using $a_1$, find whether the point is from class 1 or from class 2. If $a_1 < 0.5$, then a point from class 1 is generated. Otherwise, a point from class 2 is.

Step 3: If the point is generated from class 1, find $x$ and $y$ in the following way.

$$z = 0.a_2a_3a_4a_5_a_6$$

$$x = \sqrt{\frac{z}{2}}; \quad 0 \leq z \leq 0.5$$

$$= 1 - 0.5\sqrt{4 - 2(1 + z)}; \quad 0.5 \leq z \leq 1$$

$$z = 0.a_7a_8a_9a_{10}a_{11}$$

$$y = \sqrt{\frac{z}{2}}; \quad 0 \leq z \leq 0.5$$

$$= 1 - 0.5\sqrt{4 - 2(1 + z)}; \quad 0.5 \leq z \leq 1$$

Step 4: If the point is from class 2, find $x$ and $y$ such that,

$$z = 0.a_1a_2a_3a_4a_5_a_6$$

$$x = \sqrt{\frac{z}{2}} + 1.1; \quad 0 \leq z \leq 0.5$$

$$= 1 - 0.5\sqrt{4 - 2(1 + z) + 1.1}; \quad 0.5 \leq z \leq 1$$

$$z = 0.a_7a_8a_9a_{10}a_{11}$$

$$y = \sqrt{\frac{z}{2}}; \quad 0 \leq z \leq 0.5$$

$$= 1 - 0.5\sqrt{4 - 2(1 + z)}; \quad 0.5 \leq z \leq 1$$

Step 5: Repeat the process 1000 times for generating thousand points.
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2.3.1.2 Results on the created artificial dataset

From the above distribution 20 different sets of 1000 points are generated. For each such set of points, the 2D histogram is formed and the clustering was done. For such dataset, the histogram containing 1000 points is shown in Figure 2.1, and the clustering obtained is shown in Figure 2.2.

| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1 0 0 1 1 1 2 3 2 2 1 1 1 0 1 2 3 4 5 5 4 3 2 0 |
| 2 0 1 1 1 3 6 9 9 6 3 1 1 2 4 7 10 12 13 12 0 6 2 |
| 3 0 2 0 10 14 16 10 15 8 6 3 2 5 9 16 23 27 26 22 16 0 4 |
| 4 1 6 11 15 21 28 27 23 16 10 5 4 9 15 24 33 39 38 31 23 14 7 |
| 5 3 0 14 23 31 38 35 32 22 13 6 6 10 20 32 45 56 55 50 37 23 10 |
| 6 3 0 17 27 35 44 41 38 36 28 15 8 6 12 24 39 55 66 62 54 41 26 13 |
| 7 2 9 15 23 34 42 45 39 26 15 9 7 13 24 39 51 58 62 52 35 22 10 |
| 8 2 6 12 19 29 32 34 27 21 12 7 5 12 20 39 48 52 41 30 18 8 |
| 9 2 5 10 16 22 29 26 21 15 9 6 5 0 15 23 30 35 34 28 20 13 6 |
| 10 1 3 6 10 12 16 15 12 10 6 4 3 5 9 13 18 28 19 18 13 8 4 |
| 11 1 1 3 4 6 6 7 6 4 3 2 2 2 4 6 6 9 9 7 6 4 2 |

Figure 2.1: 2D Histogram with artificial dataset

| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 |
|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| 1 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 | 1 1 1 1 1 |
| 2 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 | 1 1 1 1 1 |
| 3 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 | 1 1 1 1 1 |
| 4 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 5 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 6 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 7 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 8 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 9 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 10 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |
| 11 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 | 1 1 1 1 1 |

Figure 2.2: Processed histogram of artificial dataset showing two clusters
From the Figure 2.2, it may be observed that there are two clusters and the boundary between them corresponds to the intervals 11 and 12 for the variable $x$. Interval 11 corresponds to the interval $(0.95, 1.05]$ and interval 12 corresponds to $(1.05, 1.15]$. This is the expected actual result, since $x < 1$ indicates that the corresponding point should go to class 1, and $x > 1.1$ indicates that the corresponding point should go to class 2.

The algorithm is verified on 19 other recorded sets of 1000 points. Each time, the proposed method provided the expected result.

2.3.2 Experiments and results on the color and IR face image datasets

For the application of the developed technique for the detection of facial features, the cluster with the largest number of bins corresponds to the skin color. Our cluster of interest is the second largest cluster containing the feature sets (two eyes, nose and mouth) as the connected components. The cluster with the largest number of members (skin portion of face) is thus removed and the second largest cluster, which normally contains the portions corresponding to two eyes, nose and mouth is considered as the three basic features of the face.

2.3.2.1 Description of datasets used

Datasets considered for forming the 2D and 3D histograms are (i) IRIS Thermal / visual dataset [139] and (ii) AR color dataset [140].
IRIS Thermal/visual dataset:

The description of the dataset along with a few sample images is given in Appendix A. For the present experiment, the frontal and slightly moved faces (5 out of 11) of 'exp1', 'exp2' folders and '2on' subfolder of illumination folder for each person, are selected for testing. All images are of a single person with the same background. Face portions are cropped to dimension 90 \times 100 for all 30 classes. RGB color bands are extracted and all 2D and 3D histograms are computed. Feature set is also extracted in each case.

AR dataset

AR dataset contains 120 face classes with 13 face images (both male and female) in each face class. The description of the dataset along with a few sample images are given in Appendix A. For the experiment, the first 40 face classes are considered. Since frontal faces with detailed facial features are required, images with veil are not considered. The images with indices (8-13) contain artifacts and veil, and hence those images are not taken for the experiment. Out of the 13 images, faces with indices (1,2,3,4,5,6,7) which contain changes in expression and illumination, are selected. All images have white background and are cropped to size 100 \times 100.

2.3.2.2 Experimental stages and remarks

Two stages of experiments are carried out to establish the process of multivariate image segmentation. In stage 1, the proposed algorithm is applied on the histogram(s) to obtain the facial features as segmented parts of the image. In stage 2, the dimensionality reduction and the classification are
performed on the segmented parts using the nearest neighbor classifier. That is, in the stage 2, the utility of the proposed method for segmentation is verified for classification accuracy. The details of these stages are discussed below.

**Stage 1:**

In this stage of experiment, the vector values (R,G,B) for each pixel of AR imagery or the vector values (R,G,B,IR) of IRIS thermal/visual dataset, for each face image are provided as input for multivariate histogram segmentation algorithm. The features of the face images are segmented and initially three largest segments are formed. The second largest segment is normally selected to contain the feature set.

![Figure 2.3: RGB face images from AR dataset and corresponding extracted feature segments using bivariate histogram](image-url)
In Figure 2.3, the images in the first column are representative RGB images from AR dataset. The images in the second column are the images obtained containing the extracted features. In Figure 2.4, the images in the first column are representative color images from visual/IRIS data set. The images in the second column are the IR counterparts of the images of the first column. The images in the third column depict the feature extracted images obtained due to the segmentation procedure undertaken.

Figure 2.4: RGB and IR face images from IRIS visual/thermal dataset and corresponding extracted feature segments using trivariate histogram

Remarks:

1. For AR face dataset, for each image, 3 bivariate histograms can be formed. As the separation between blue and red wave lengths is high, the experiment justifies that the bivariate histogram with red and blue variables provides
better results in distinguishing the facial features more effectively.

2. For the thermal visual dataset, among the six bivariate histograms, the histogram corresponding to the combination of IR and blue bands is found to provide better results, because of the same reason as stated. For 3D histograms, the best combination is found to be the histogram with R, G and IR bands.

3. Inclusion of IR band is found to increase the quality of the feature set. That is, the results of the experiment on 3D histogram containing IR band along with R and B bands is found to be better than other 2D and 3D combinations of histograms.

4. In case of AR data set, it may be noted that the images with different illumination are included in the tests.

5. It may also be stated that the feature in the IRIS-IR data set is illumination invariant. However, the folder ‘2on’ contains images with different illumination.

Stage 2:

This part of the experiment shows the utility of the segmentation for the recognition of faces. The features like eyes, nostrils, and lip portions are extracted to obtain T structure and the T structure is dimensionally reduced by subspace methods [141] [17]. The recognition rates using these reduced features are found to be better than the dimensionality reduction schemes without using the T structure. The feature sets are automatically segmented out from the other face portions in Stage I and those are used for dimensionality reduction.
using subspace based methods (PCA and 2DPCA). The nearest neighbor algorithm is used for classification [84].

### 2.3.3 Utility of facial features

Two experiments are carried out to establish the utility of the method. In the first experiment, only the obtained facial features are used for dimensionality reduction and classification. In the second experiment, the complete images are used for dimensionality reduction and classification.

The training and test sets are selected from IRIS and AR dataset in the following way:

**Training Set:** From IRIS Thermal/visual dataset, the number of face classes considered are 30. Two images from each of the ex1, ex2 and 2on data folders are selected as training set. These $2 \times 3 = 6$ images are all frontal faces. Thus the total number of images in training set is $30 \times (2$ images of ex1+2) images of ex2+2 images of 2on) totalling to 180.

For AR dataset, the number of face classes considered is 40. These are the first 40 classes in the database. The images included in the training set are those images with indices 1, 2, 3 and 4. Thus, the sizes of the training is 160.

**Test Set:** From IRIS Thermal/visual dataset, three images from each of the ex1, ex2 and 2on data folders are selected as test set. These $3 \times 3 = 9$ images are all frontal faces. The total number of images in the test set is $30 \times (3$ images of ex1+3 images of ex2+3 images of 2on) totalling to 270.
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For AR database, those images with indices 5, 6, and 7 are used as test set. Thus, the sizes of the test sets is 120.

After the training-test division of datasets, both the datasets are processed through phase I and the feature portions are segmented out. Some of these images are shown in the second column of Figures 2.3 and 2.4.

PCA and 2DPCA are applied on the training set of the original and the segmented image set. The number of dimensions after reduction using PCA (or 2DPCA) for IRIS dataset is 180, when the segmented images are only used or the full image are used for reduction. The number of dimensions after reduction for AR dataset is 160. The reduced values of dimension are intentionally considered to be the same to maintain parity during comparison. The test image set of original and the segmented test faces are projected to the corresponding face spaces. The nearest neighbor classifier is used for classification.

Table 2.1 shows the results on both the original images and the images generated by the proposed algorithm. The experimental results in Table 2.1 show that the selected feature set images outperform the original image set when the PCA based face recognition method is applied.

Table 2.1: Comparative study of recognition rates using full image and segmented images

<table>
<thead>
<tr>
<th>Method applied</th>
<th>Dataset</th>
<th>Recognition rate using full image</th>
<th>Recognition rate using segmented image</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>IRIS</td>
<td>88</td>
<td>91</td>
</tr>
<tr>
<td>2DPCA</td>
<td>IRIS</td>
<td>92</td>
<td>94.5</td>
</tr>
<tr>
<td>PCA</td>
<td>AR</td>
<td>92</td>
<td>94.8</td>
</tr>
<tr>
<td>2DPCA</td>
<td>AR</td>
<td>93.5</td>
<td>95</td>
</tr>
</tbody>
</table>
Remarks:

The basic observation on the proposed technique of the multivariate histogram segmentation is that (R,B) offers the best performance among all 2-feature combinations on AR dataset, (IR,B) works the best among all 2-feature combinations on IRIS dataset, and (IR,G,B) performs best among all 3-feature combinations for IRIS dataset. In these cases the feature set is more distinctly found.

There are 6 pairs of color bands for IRIS data and the correlation coefficient can be calculated for each pair. Among these pairs, it is possible to select those bands which preserve the maximum information. Such combinations are more suitable for constructing the multivariate histograms than other correlated bands. Since B and IR are maximally separated according to their wavelength than any other combination, B and IR combination is chosen for IRIS data. Similarly, R and B are chosen for the AR data.

Note also that, in each data set, images with different illuminations are included. The obtained results using the proposed method are found to provide better recognition rates even under variations in illumination. Thus the proposed is seen to overcome the restriction of illumination variations to a great extent.

2.4 Conclusions

The suggested approach for segmenting the image using histograms is unsupervised. Each one of the four univariate histograms (corresponding to the
four channels) has a single mode and thus segmentation based upon finding valleys in a histogram becomes a difficult task. Further, a smoothing technique is applied on histograms to remove the spurious peaks. The peaks are used to get the major segments and one can use the valley regions for edge detection purpose. The method of facial feature extraction using histograms is independent of feature position. It is also illumination invariant to a great extent. The performance of the 2D histogram processing for the face images is superior to the 1D histogram because more information is used, and hence the valley regions are much clearer. The performance of the method is verified on an artificial dataset and applied on the color AR face and IR face datasets. The segmented face images thus obtained, contain the skin portion.

In 3D case, when combinations of RGB color channels are taken, the clusters are distinguishable. Moreover, IR channel gives better and distinct results as thermal imageries are illumination invariant. IR images in combination with other color bands used in the multivariate histogram segmentation results in considerable improvement in generating feature set. However, if IR face images are with spectacles on eye, then the univariate segmentation algorithms fails to detect eye portions.

The computational complexity of constructing a multivariate histogram is higher than that of a univariate histogram. However, as expected, the multivariate histogram provides more information than the univariate histogram. The time consuming part of the algorithm is related to the histogram processing - when the peak searching algorithm is run. For each cell \((3^2 - 1)\) neighboring bins need to be compared. Thus, for an n-variate histogram, searching time complexity is
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\[ O(256^n(3^n - 1)) = O(768^n) \], where the number of different gray levels in each dimension is considered to be 256. Actually, the search effort increases rapidly with histogram dimensionality in checking the father-child relationship of bins. This is the reason for not using 4D histogram for the thermal and visual dataset. The manageable numbers for \( n \) are therefore, 2 and 3.