Chapter 6

Class specific subspace based nonlinear correlation filter

6.1 Introduction

There are other problems of using linear correlation filters for face recognition purposes. The linear filter formulation considers images having nonuniform dynamic range and hence in the testing stage it is hard to discriminate authentic and impostor images that lie below a span of low grey level. To overcome this situation this paper proposes nonlinear correlation filter by exploiting the point nonlinearities [161] of image pixels so that the designed correlation filter achieves a uniform dynamic range. This type of nonlinear mapping stretches pixel distribution of face images in a wide range and consequently high frequency components are amplified. In this study three approaches are judiciously combined to improve face recognition results under illumination variations viz, i) projection based method of designing correlation filter is used to improve upon the capability of recognition at all possible illumination variations ii) phase correlation method is used to enhance peak sharpness at the correlation plane for

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\[ \text{already described in Chapter-5} \]
authentic face image as phase contains more information than the magnitude of spectrum and iii) point nonlinearities are considered to extend uniform dynamic range. To achieve these two correlation filters are designed (a) nonlinear optimum projecting image correlation filter $H_p$ and (b) nonlinear optimum reconstructed image correlation filter $H_r$. The nature of design process of these two filters is same with only difference in image used for synthesis. Design of $H_p$ uses projecting image and the design of $H_r$ includes reconstructed image. The phase correlation between these two filters produces a response surface, the nature of which totally depends on the face class involved. Ideally a delta type peak at the correlation plane is obtained if these two filters are generated from the same face class. Experimental results on standard databases like YaleB (extended)[142] and PIE database[143] witness the promising performance of the proposed method when compared to other standard correlation filter based face recognition systems.

6.2 Formulation of nonlinear correlation filters

6.2.1 Nonlinear optimum projecting image correlation filter

Any projecting image from $k$th (where, $k = 1, 2, \cdots, M$) class is represented in spatial domain as $T$ (in matrix form) or $t$ (in vector form) and its frequency domain counterparts are $\bar{T}$ and $\bar{t}$ respectively. $\bar{T}$ represents the diagonal form of $\bar{t}$. The point wise nonlinearities of an image can be achieved according to power law transformation given by,

$$t_\alpha^\beta = \alpha^\beta$$  \hspace{1cm} (6.1)

where, $\alpha > 0$, can take any integer value and $\beta > 0$, can be integer or fraction.

Eq.(6.1) tells that each element of $t$ is scaled by $\alpha$th amount and raised to $\beta$th power. Hence for $\alpha = \beta = 1$, the image $t^1_1$ represents the original image $t$. If
6.2. **Chapter 6 : Nonlinear optimum projecting image correlation filter**

\( h_{\alpha \beta} \) is the optimum correlation filter corresponding to projecting image \( t^\beta_\alpha \), then the correlation plane \( g_{\alpha \beta} \) in response to \( t^\beta_\alpha \) is given by,

\[
g_{\alpha \beta} = \bar{T}^{\beta*}_\alpha h_{\alpha \beta}
\]  

(6.2)

where \( * \) represents conjugation operation.

From Eq. (6.2), it can be noted that a number of correlation planes \( g_{\alpha \beta} \) as well as a number of classifiers \( h_{\alpha \beta} \) is generated for each value of \( \alpha = \alpha_1, \ldots, \alpha_n \) and \( \beta = \beta_1, \ldots, \beta_m \) in response to a single projecting image. The same can be written as,

\[
\bar{T}^{\beta_1}_{\alpha_1}, \bar{T}^{\beta_2}_{\alpha_1}, \ldots, \bar{T}^{\beta_m}_{\alpha_1}; \bar{T}^{\beta_1}_{\alpha_2}, \bar{T}^{\beta_2}_{\alpha_2}, \ldots, \bar{T}^{\beta_m}_{\alpha_2}; \ldots; \bar{T}^{\beta_1}_{\alpha_n}, \bar{T}^{\beta_2}_{\alpha_n}, \ldots, \bar{T}^{\beta_m}_{\alpha_n}.
\]

Hence from Eq. (6.2) a set of correlation planes can be written as,

\[
\begin{align*}
g_{\alpha_1 \beta_1} &= \bar{T}^{\beta_1*}_{\alpha_1} h_{\alpha_1 \beta_1} \\
g_{\alpha_1 \beta_2} &= \bar{T}^{\beta_2*}_{\alpha_1} h_{\alpha_1 \beta_2} \\
\vdots &= \vdots \\
g_{\alpha_n \beta_m} &= \bar{T}^{\beta_m*}_{\alpha_n} h_{\alpha_n \beta_m}
\end{align*}
\]

(6.3)

Since a sharp and distinct correlation peak in correlation plane reduces the chances of misclassification, minimization of energy at the correlation plane [7] containing undesired side lobes and maximization of correlation peak height[10] are necessary. This criteria helps in amplifying the high frequency components of the projecting image of which the point wise nonlinear transformation is done. Hence for selected variations of \( \alpha \) and \( \beta \), correlation plane energy could be evaluated for each correlation
plane indicated in Eq. (6.3) as,

\[
|g_{\alpha_1 \beta_1}|^2 = |T_{\alpha_1}^{\beta_1} h_{\alpha_1 \beta_1}|^2 = h_{\alpha_1 \beta_1}^+ T_{\alpha_1}^{\beta_1} h_{\alpha_1 \beta_1}
\]

\[
|g_{\alpha_1 \beta_2}|^2 = |T_{\alpha_1}^{\beta_2} h_{\alpha_1 \beta_2}|^2 = h_{\alpha_1 \beta_2}^+ T_{\alpha_1}^{\beta_2} h_{\alpha_1 \beta_2}
\]

\[
\vdots = \vdots
\]

\[
|g_{\alpha_n \beta_m}|^2 = |T_{\alpha_n}^{\beta_m} h_{\alpha_n \beta_m}|^2 = h_{\alpha_n \beta_m}^+ T_{\alpha_n}^{\beta_m} h_{\alpha_n \beta_m}
\] (6.4)

Hence to get a sharp peak in each correlation plane for selected variations of \(\alpha\) and \(\beta\), it is needed to minimize the correlation energies separately, with respect to \(h\), given in Eq. (6.4). Minimization of the correlation plane energy is reflected by the following performance criteria of the desired filter \(h_{\alpha \beta}\) and is given by,

\[
\min \left\{ h_{\alpha \beta}^+ T_{\alpha}^{\beta} h_{\alpha \beta} \right\}
\] (6.5)

Minimization of the performance criteria, indicated in Eq. (6.5), is evaluated with respect to \(h\). It can be noted that the expression in Eq. (6.5) is different from the standard performance criteria of MACE filter, since a set of classifiers has been taken into consideration using point nonlinearities in addition to different scaled magnitudes of image pixels. Now origin value or the peak value of the correlation plane in response to the projecting image \(t_{\alpha}^{\beta}\) can be formulated in frequency domain as, \(t_{\alpha}^{\beta} + h_{\alpha \beta}\). In addition to suppressing side lobes of the correlation peak, which can be achieved by Eq. (6.5), it is necessary for an optimum filter to yield large peak value at the origin of the correlation plane. This condition is met by maximizing projecting image correlation peak intensity with respect to \(h\) for a typical set of \(\alpha, \beta\), as,

\[
\max \left\{ |t_{\alpha}^{\beta} + h_{\alpha \beta}|^2 \right\}
\] (6.6)

Hence, to get optimum correlation filter \(h_{\alpha \beta}\), the optimal tradeoff performance crite-
rion can now be set as,

\[ J(h_{\alpha\beta}) = \frac{|t_\beta + h_{\alpha\beta}|^2}{h_{\alpha\beta}^* T_\alpha h_{\alpha\beta}} \]  \hspace{1cm} (6.7)

The criterion can be obtained as the dominant eigenvector \([10]\) of \(\{T_\alpha^* T_\alpha\}^{-1} t_\alpha^* t_\alpha^+\).

The desired filter is therefore given by,

\[ h_{\alpha\beta} = \{T_\alpha^* T_\alpha\}^{-1} t_\alpha^+ \]  \hspace{1cm} (6.8)

For different values of \(\alpha\) and \(\beta\), Eq.(6.8) can be expanded and expressed in a closed form solution as,

\[
\left( \begin{array}{c}
h_{\alpha_1\beta_1} \\
h_{\alpha_1\beta_2} \\
\vdots \\
h_{\alpha_n\beta_m}
\end{array} \right) = \left( \begin{array}{cccc}
P_{\alpha_1\beta_1} & 0 & \cdots & 0 \\
0 & P_{\alpha_1\beta_2} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & P_{\alpha_n\beta_m}
\end{array} \right)^{-1} \left( \begin{array}{c}
t_{\alpha_1} \\
t_{\alpha_1} \\
\vdots \\
t_{\alpha_n}
\end{array} \right)
\]  \hspace{1cm} (6.9)

where \(P_{\alpha\beta} = T_\alpha^* T_\alpha\).

Denoting block vectors and matrix as,

\[
[h_k^p] = \left( \begin{array}{c}
h_{\alpha_1\beta_1} \\
\vdots \\
h_{\alpha_n\beta_m}
\end{array} \right), \quad [\tilde{P}] = \left( \begin{array}{cccc}
P_{\alpha_1\beta_1} & 0 & \cdots & 0 \\
0 & P_{\alpha_1\beta_2} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & P_{\alpha_n\beta_m}
\end{array} \right), \quad [t] = \left( \begin{array}{c}
t_{\alpha_1\beta_1} \\
\vdots \\
t_{\alpha_n\beta_m}
\end{array} \right)
\]

Eq.(6.9) can be redrawn as,

\[ [h_k^p] = [\tilde{P}]^{-1} [t] \]  \hspace{1cm} (6.10)

where \([h_k^p]\) correspond to projecting image from \(k\)th class.

As \([\tilde{P}]\) is a block matrix in diagonal form, the decoupled nature of \(h_{\alpha\beta}\) is accomplished, i.e. \(h_{\alpha_1\beta_1}\) depends only on \(t_{\alpha_1}^+\) and no other variations of \(\alpha\) and \(\beta\) are allowed.
It can also be stated that $h_{\alpha_i \beta_l}$ ($0 < i \leq n$, $0 < l \leq m$) depends on the nonlinear characteristic of image pixels in $t_\alpha^\beta$ with respect to the original pixels distribution in $t$ and $h_{\alpha_i \beta_l}$ is optimally designed with the performance criteria given in Eq.(6.5) and Eq.(6.6). In addition to that $h_{\alpha_i \beta_l}$ is generated from the projecting image. Hence the designed filter given in Eq.(6.10) can be termed as nonlinear optimum projecting image correlation filter or NOPICF.

The 2D correlation filter $H_{\alpha_i \beta_l}$ ($0 < i \leq n$, $0 < l \leq m$) is obtained by reshaping the filter vector $h_{\alpha_i \beta_l}$ in proper row-column order. Hence by block matrix form 2D-NOPICF for $k$th class projecting image is expressed as,

$$
[H^k_p] = \begin{pmatrix}
H_{\alpha_1 \beta_1} \\
H_{\alpha_1 \beta_2} \\
\vdots \\
H_{\alpha_n \beta_m}
\end{pmatrix}
$$

(6.11)

where suffix $p$ represents that the filters are synthesized with projecting image.

Eq.(6.11) also indicates that the desired 2D-NOPICF $[H^k_p]$ is a collection of nonlinear classifiers.

### 6.2.2 Nonlinear optimum reconstructed image correlation filter

To reconstruct the projecting image it is necessary to develop the class specific subspace. Hence the subspace analysis is made over $j$th class ($j = 1, 2, \ldots, M$) where each class contains $N$ number of lexicographic ordered training vectors $x_i$ of dimension $d \times 1$. As the least significant eigenvector is sensitive to noise [160] and may give error during reconstruction, this is discarded from the generated subspace. Therefore, the truncated subspace $E^j$ is formed as,

$$
E^j = [e_1, e_2, e_3, \ldots, e_{(N-1)}]_{d \times (N-1)}
$$

(6.12)
where \( e_i \)s are the orthonormal vectors and superscript \( j \) indicates that the subspace is originated from \( j \)th class training images.

Since the projecting image can be from any class, the \( k \)th class test image is considered as the projecting image. During reconstruction of face images, the difference vector of non linearly mapped projecting vector \( t^\beta_{\alpha_i} \) \((0 < i \leq n, 0 < l \leq m)\) is obtained as,

\[
s^\beta_{\alpha_i} = t^\beta_{\alpha_i} - m \tag{6.13}
\]

where \( m \) is the average image vector of original training variations \((x_i)\).

Projecting \( s^\beta_{\alpha_i} \) into the subspace \( E^j \), the weight vector \( \omega^\beta_{\alpha_i} \) is obtained as,

\[
\omega^\beta_{\alpha_i} = (E^j)^T s^\beta_{\alpha_i} \tag{6.14}
\]

where \( T \) represents transpose operation.

The reconstructed version \( r^\beta_{\alpha_i} \) corresponding to the test vector \( t^\beta_{\alpha_i} \) is obtained as,

\[
r^\beta_{\alpha_i} = m + \sum_{i=1}^{N-1} e^j_i \omega^\beta_{\alpha_i} \tag{6.15}
\]

For different values of \( \alpha \) and \( \beta \), a set of reconstructed vectors are formed. It is easier to represent these vectors in block vector form as,

\[
[r^{jk}] = 
\begin{pmatrix}
  r^\beta_{\alpha_1} \\
  r^\beta_{\alpha_2} \\
  \vdots \\
  r^\beta_{\alpha_n}
\end{pmatrix}
\tag{6.16}
\]

The superscript \( jk \) in Eq.(6.16) represents the reconstructed vectors correspond to \( k \)th class test image while projected on \( j \)th class subspace. The reconstructed image \( R^\beta_{\alpha} \) in space domain can be obtained by reshaping the vector \( r^\beta_{\alpha} \) in proper row-column
order. The frequency domain transformation of the reconstructed image \( R^\beta_\alpha \) is simply obtained as,

\[
R^\beta_\alpha = \sum_{p=0}^{d_1-1} \sum_{q=0}^{d_2-1} R^\beta_\alpha(p, q) e^{-\frac{j2\pi up}{d_1}} e^{-\frac{j2\pi vq}{d_2}}
\]  

(6.17)

From Eq.(6.17) the NORICF is formed in the same way as NOPICF is designed. Instead of \( T^\beta_\alpha \), however, \( R^\beta_\alpha \) is used for NORICF design. A number of NORICFs are formed for different values of \( \alpha \) and \( \beta \) as obtained in case of NOPICFs. Hence with the help of Eq.(6.11) the block matrix form of 2D-NORICF is written as,

\[
[H^{jk}] = \begin{pmatrix}
H_{\alpha_1\beta_1} \\
H_{\alpha_1\beta_2} \\
\vdots \\
H_{\alpha_n\beta_m}
\end{pmatrix}
\]  

(6.18)

where suffix \( r \) represents the reconstructed images used during NORICF synthesis.

### 6.3 Face recognition analysis using correlation classifiers

From Eq.(6.11) and Eq.(6.18) it is safe to comment that theoretically a delta type correlation peak can be obtained due to correlation between \([H^k_p]\) and \([H^{jk}_r]\) when \( j = k \). However, it may be noted that \([H^k_p]\) and \([H^{jk}_r]\) are block matrices and therefore these filters contain several classifiers depending on the values of \( \alpha \) and \( \beta \). Hence one-to-one correlation is needed to get the respective correlation planes as shown in Fig.(6.1). From a set of correlation planes, PSRs are evaluated and the maximum one is considered for decision. The detail of the proposed filtering technique and decision making process regarding authentication is given in the block diagram shown in Fig.(6.1). It is evident from Fig.(6.1) multicorrelation approach is performed here for a single input image to evaluate the maximum PSR value. Though the illumination of the image mostly influences the magnitude spectrum yet, a major benefit is accrued
by obtaining the phase spectrum.

As the poorly illuminated images contain more energy at low frequencies, the phase spectrum analysis of these images is a logical choice. As delta type correlation plane is desired for reducing classification errors, \( \delta(m, n) \) is represented by a constant flat Fourier transform plane. This can be achieved if and only if phase only NOPICF is identical to phase only NRICF i.e. all the phases are canceled out resulting in a constant flat spectrum. Hence, phase correlation between NOPICF and NRICF gives better results when compared to classical frequency domain correlation.

### 6.4 Test results

PIE database contains two illumination subsets with 68 subjects and 21 images per subject. \( 640 \times 486 \) pixel color images are converted into gray scale images as the intensity is the main concern. All images are cropped to the size of \( 128 \times 128 \). No other preprocessing is done. YaleB(extended) database contains 38 different persons and for each person 64 differently illuminated gray scale frontal face images of size \( 192 \times 168 \) are present. These images are resized to \( 100 \times 100 \). According to the lighting
direction and camera position each individual’s images are categorized into 5 subsets.

6.4.1 Comparative study on discriminating performances

In the first set of experiment, the discrimination ability of the proposed filter between an authentic and impostor face image is tested. The phase extended UMACE (PE-UMACE) and OTMACH\[13\] (PE-OTMACH) filters are designed with typical set of training images and multicorrelation approach is considered with one non-trained authentic image. In multicorrelation approach, a set of correlation planes are developed corresponding to a test image for different values of $\alpha$ and $\beta$, while correlated with the designed PE-UMACE and/or PE-OTMACH. The same set of images are considered for training and testing in proposed method. It is to be noted that when image is multiplied with a scalar value $\alpha$, basically a linear operation is performed, i.e., the scaled image pixels will have the same dynamic range as the original one, if it is normalized within the range of gray level intensity $[0 - 255]$ and no change in correlation plane will be observed. Hence throughout this study $\alpha$ is set to 1. The change in correlation plane can be observed if image pixels are raised to $\beta$th amount as the image will be nonlinearly mapped with respect to the original one. In this study values of $\beta$ is set to 1 (to retain the original one) and 0.1, 0.2, 0.3 (empirically) so that a narrow range of low intensity values are mapped into a wide range of high intensities and relatively high dynamic range of images and so also correlation filters can be achieved. Values such that $\beta > 1$ are ignored as low intensity images will be more darker and consequently discrimination capability of correlation filters will be lost.

A set of NOPICFs and NORICFs are evaluated corresponding to the test image for different values of $\alpha$ and $\beta$. Each NOPICF is correlated with corresponding NORICF. From the set of response surfaces for all filters i.e. PE-UMACE, PE-OTMACH and the proposed one, the correlation plane associated with maximum PSR value is taken for
making the decision of authentication. These correlation planes are shown in Fig. (6.2).

From Fig. (6.2a), Fig. (6.2c) and Fig. (6.2e) it is observed that the response surface corresponding to proposed method as shown in Fig. (6.2e) gives better discrimination ability comparing to other filters. The nature of correlation plane corresponding to Fig. (6.2e) contains sharp and distinct peak with high value and low sidelobes. This criteria is helpful in discriminating the authentic face images, which is reflected in Figs. (6.2b,d,f). The PSR values for impostors are shown with surface boundary of PSR=10. It may be noted that many of impostors are falsely accepted as authentic in case of PE-UMACE and PE-OTMACH, as their PSR values are above 10. Considering Fig. (6.2b,d), it is observed that very less number of impostors are falsely accepted as authentic while the proposed method is employed and this is justified by Fig. (6.2f).

6.4.2 Comparative performance based on PSR distribution

To show the better verification performance of the proposed approach comparing to the standard filters, a 20 set of 3 randomly chosen training images are taken and the top-left corner image of Subset-5 (Fig. (A.3)) is taken for testing. Obviously this test image is not included in 20 set during training of filters. Table. (6.1) shows the promising performance of the proposed filter as verification classifier with a PSR threshold value of 10. In each training set the PSR value obtained from proposed method is greater than 10 which is not so for other filters. Hence it can be concluded from Table. (6.1) that false rejection rate is improved with the proposed approach.

To test the verification performance of the proposed method the authentic PSR distribution is made with the help of sample order statistics. To develop this experiment 10 individuals are randomly chosen from 38 face images. For each individual 20 sets of training images are taken to synthesize all filters along with the proposed scheme. Hence for each individual $20 \times 64$ authentic PSR (APSRs) are obtained and
then averaged. Having obtained APSR matrix of size $10 \times 64$ for 10 individuals, the normal distribution plot is made. This procedure is repeated for each standard filtering method along with the proposed one. Fig.(6.3) shows the probability distribution plots for four different filtering methods. For matrix APSR, normal probability dis-
Table 6.1: The PSR value comparison of different filters correspond to one unseen authentic image for 20 different training sets.

<table>
<thead>
<tr>
<th>Training Sets</th>
<th>MACH</th>
<th>UMACE</th>
<th>OTMACH</th>
<th>PEUMACE</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>47,53,5</td>
<td>8.4226</td>
<td>10.1632</td>
<td>9.9003</td>
<td>17.3128</td>
<td>23.0935</td>
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<tr>
<td>20,63,24</td>
<td>4.664</td>
<td>7.8933</td>
<td>6.7052</td>
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<td>13.0181</td>
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<td>32,22,58</td>
<td>6.1131</td>
<td>11.6095</td>
<td>10.1757</td>
<td>10.0449</td>
<td>18.5307</td>
</tr>
<tr>
<td>3,2,34</td>
<td>5.0989</td>
<td>6.9466</td>
<td>5.325</td>
<td>11.183</td>
<td>24.2187</td>
</tr>
<tr>
<td>61,16,38</td>
<td>11.9977</td>
<td>13.9295</td>
<td>12.8193</td>
<td>22.0452</td>
<td>29.4638</td>
</tr>
<tr>
<td>44,39,8</td>
<td>6.24</td>
<td>6.0387</td>
<td>6.8613</td>
<td>10.5529</td>
<td>18.49</td>
</tr>
<tr>
<td>5,9,51</td>
<td>4.8421</td>
<td>7.3242</td>
<td>5.373</td>
<td>14.7871</td>
<td>21.1288</td>
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<tr>
<td>55,45,7</td>
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<td>61,17,27</td>
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<td>60,5,17</td>
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<td>10.4287</td>
<td>9.9073</td>
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<td>52,33,41</td>
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<td>39,8,34</td>
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<td>0</td>
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<td>17.3505</td>
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<td>19,6,26</td>
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<td>0</td>
<td>5.6837</td>
<td>0</td>
<td>20.9853</td>
</tr>
</tbody>
</table>

Distribution plot displays a line for each column of APSR. The straight line indicates that the data originates from a normal distribution. Curvature indicates departure from normal distribution. Better linearity is obtained from 10 to 50 PSR values for the proposed method. Therefore better normal distribution is achieved comparing to other filters. At the higher end of the distribution, the PSR data for the proposed system is stretched out relative to the normal distribution. This indicates higher PSR values compared to others filters. Again from the probability plot it is observed that the PSR values become zero for authentic image in case of other correlation filters, which is not so for the proposed method.
6.4. Chapter 6: Test results

![PSR Data](image)

Figure 6.3: Probability distribution of authentic PSRs for different filters. Better distribution with high values of PSRs are obtained with proposed approach comparing to others.

6.4.3 Performance analysis using ROC

To further evaluate face verification performance of the proposed system both the databases are considered. Out of 21 faces from one individual as shown in Fig. (a), only two images with image index 10 and 19 are taken for training. Another two training images are taken from YaleB subset-1. The logic behind of training these images is that these images have no extreme variation of lighting. Hence the synthesized filters (including the proposed system) in both the training cases have no idea of extreme illumination variation of faces as these are excluded from training.
The performance of correlation filters are characterized, in terms of the $P_D$ and $P_{FA}$ with the help of ROC curves. To observe the robustness of proposed face recognition system the faces (excluding 10 and 19 in case of PIE and excluding subset-1 in case of YaleB) are taken for testing and ROCs are plotted as shown in Fig.(6.4a,b). The conventional bi-normal model is used to fit smooth ROC curves. From Fig.(6.4a,b) it is observed that the ROC corresponding to the proposed technique gives better traces of step function comparing to other filters. This indicates better illumination tolerance capability of the proposed system than the other standard nonlinear filters.

<table>
<thead>
<tr>
<th>Training</th>
<th>PE-MACH</th>
<th>PE-UMACE</th>
<th>PE-OTMACH</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC</td>
<td>0.774</td>
<td>0.82</td>
<td>0.76</td>
<td>0.943</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.6919-0.857</td>
<td>0.74-0.892</td>
<td>0.674-0.844</td>
<td>0.899-0.985</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Training (CY)</th>
<th>PE-MACH</th>
<th>PE-UMACE</th>
<th>PE-OTMACH</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
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<td>AUC</td>
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<td>0.851</td>
<td>0.91</td>
<td>0.925</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.8-0.931</td>
<td>0.782-0.920</td>
<td>0.856-0.964</td>
<td>0.875-0.974</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Training (PIE)</th>
<th>PE-MACH</th>
<th>PE-UMACE</th>
<th>PE-OTMACH</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC</td>
<td>0.898</td>
<td>0.874</td>
<td>0.955</td>
<td>0.996</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.841-0.955</td>
<td>0.811-0.938</td>
<td>0.917-0.99</td>
<td>0.985-1.0</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Training (PIE)</th>
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<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC</td>
<td>0.924</td>
<td>0.906</td>
<td>0.978</td>
<td>0.995</td>
</tr>
<tr>
<td>95% CI</td>
<td>0.874-0.973</td>
<td>0.851-0.961</td>
<td>0.952-1.0</td>
<td>0.982-1.0</td>
</tr>
</tbody>
</table>

Fig.(6.4c-f) shows different ROC plots for different set of training images (from YaleB) as (c) two random (d) three random, and from PIE (e) three random and (f) four random. Random images are taken 20 times and experimented over whole database of YaleB and PIE. Having obtained authentic and impostor PSRs, $P_D$ and $P_{FA}$ are calculated and ROCs are plotted. From Fig.(6.4c-f) the ROC curves corresponding to the proposed method is approaching to a step function and hence it has the better detection performance comparing to the other filters. Area under ROCs (AUC) are
Figure 6.4: ROC plots for (a) training 10 and 19 from PIE (b) training two images of subset-1 from YaleB. The improved recognition performance of proposed technique comparing to standard filters in terms of ROCs are shown with random images for (c),(d) YaleB and (e),(f) PIE. Comparisons are made with the phase extended version of standard filters with multicorrelation approach.

also calculated for Fig.(6.4c-f) so that the relative measurement of classification performance of different methods can be easily stated. As observed from Table.(6.2), in
6.5. Chapter 6: Conclusions

each case highest AUC is obtained for proposed method. The 95% confidence interval is calculated form ROCs as given in Table.(6.2). This indicates the interval in which the true AUC lies with 95% confidence.

6.4.4 Noise sensitivity

Noise sensitivity of the proposed method is further investigated as phase correlation is very much sensitive to noise. Under the inclusion of additive Gaussian noise the corrupted images are further tested with the proposed method. As noise can be characterized by variance, mean of Gaussian noise is set to 0 and different values of variance are considered as 0.001, 0.01, 0.1. From AUC plots in Fig.(6.5) it is observed that the proposed technique can tolerate illumination under noise when Fig.(6.5)(e) PIE faces are corrupted with noise variance upto 0.01 and Fig.(6.5)(f) YaleB faces are corrupted with noise variance upto 0.2, if $AUC = 0.9$ can be taken as sufficient recognition performance. It has been seen from Fig.(6.5(c),(d)) the ROC curves degrades as the variance of noise is increased in both PIE and YaleB faces. This is due to the fact phase only filters amplifies the high frequency components and whenever noise is present it is also amplified and degrades the correlation planes. One solution can be made to tolerate illumination under additive noise by proper incorporation of band-pass filter during phase only filter synthesis [162], which needs further investigation.

6.5 Conclusions

In this study a set of class dependent nonlinear classifiers (NOPICFs and NORICFs) are developed with which multicorrelation filtering is proposed for robust and effective face recognition under poor lighting condition. Nonlinearity of correlation filters are achieved by transforming image pixels according to power law transformation method which enhances the discrimination capability of proposed system as shown in Fig.(6.4c-f) and Table.(6.2). Phase correlation between nonlinear filters provides
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![Pie Image](image1)

![YaleB Image](image2)

(a) Noisy images of PIE

(b) Noisy images of YaleB

(c) ROC plots for noisy PIE

(d) ROC plots for noisy YaleB

(e) AUC plot corresponds to (c)

(f) AUC plot corresponds to (d)

**Figure 6.5**: Sensitivity of proposed filtering technique with respect to additive gaussian noise is shown for two different databases.

Distinct and sharp peak with suppressed side lobe in response to authentic is justified in Fig.(6.2e). Fig.(6.2f) also provides a clear indication of reduced misclassification rate of impostor images while proposed filtering technique is exploited. Fig.(6.4a,b) shows the better illumination tolerant capability of proposed scheme where selection of training images is not a vital issue. Performance of proposed method is compared with other standard correlation filters by multicorrelation approach and in each case the proposed system outperforms the others.