Eigenhill vs. eigenface and eigenedge

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Abstract

In this study, we present a new approach to overcome the problems in face recognition associated with illumination changes by utilizing the edge images rather than intensity values. However, using edges directly has its problems. To combine the advantages of algorithms based on shading and edges while overcoming their drawbacks, we introduced ‘‘hills’’ which are obtained by covering edges with a membrane. Each hill image is then described as a combination of most descriptive eigenvectors, called “eigenhills”, spanning hills space. We compare the recognition performances of eigenface, eigenedge and eigenhills methods by considering illumination and orientation changes on Purdue A & R face database and showed experimentally that our approach has the best recognition performance.

1. Introduction

Face recognition algorithms are based on extraction of facial features. There are essentially two types of features: partial (nose, mouth, etc.) and holistic (where each feature is characteristic of the whole face). Many face recognition algorithms can be used for extracting both partial and holistic features. Yuille et al. [1] used template matching approach for holistic feature extraction. Likewise Pentland and Turk [2] used Karhunen–Loève transformation (KLT) for extracting holistic features, which are called eigenfaces. In eigenface algorithm, the goal is to describe maximum variation among faces while reducing the high-dimensional face space to a low-dimensional eigenspace.

Though eigenfaces became popular among researchers, the idea itself is prone varying illumination like many other face recognition algorithms. There were several attempts to solve the illumination problem which are based on modeling of illumination effect on faces or finding illumination free features to describe a face. Tákacs and Wechsler proposed an edge-based approach to recognize faces using Hausdorff distance [3]. Belhumeur et al. [4] developed fischerface approach to overcome the illumination changes.

In this study, we proposed a new algorithm based on KLT to overcome problems due to illumination variation and pose changes. Our approach relies on edges that do not change considerably in varying illumination. However, edges bring their own problems, they are very sensitive to pose and orientation changes in the face. We overcome these problems by covering the edges with a membrane, which is related to regularization theory.

The organization of this paper is as follows. In the next section, a theoretical analysis of illumination effect on gray scales and edge maps is stated. In the following section, we give brief description of our method, the eigenhill. Then, performance comparisons on Purdue face database and a conclusion are given.

2. Illumination effect on face and edges

For two point light sources, one is on at a particular time, illumination change can alter the appearances of objects. To describe effect of illumination variation, we will identify the differences of two lighting patterns of an object for two distinct light sources. In the case of a lambertian surface, the image is determined by the image

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irradiance equation, \( I(x, y) = R(p, q, p_s, q_s) \), where
\[
R(p, q; p_s, q_s) = \frac{1 + pp_s + qq_s}{\sqrt{1 + p_s^2 + q_s^2}}
\]
and \( p = \partial z/\partial x, \:\: q = \partial z/\partial y \), while \( z \) is the depth map of the object. For two different light sources \((p_{s1}, q_{s1})\) and \((p_{s2}, q_{s2})\), where \( p_{s2} = p_{s1} + \delta_{p_s} \) and \( q_{s2} = q_{s1} + \delta_{q_s} \), corresponding reflectance maps will be
\[
R_1(p, q; p_{s1}, q_{s1}) = \frac{1 + pp_{s1} + qq_{s1}}{\sqrt{1 + p_{s1}^2 + q_{s1}^2}},
\]
\[
R_2(p, q; p_{s2}, q_{s2}) = \frac{1 + pp_{s2} + qq_{s2} + p\delta_{p_s} + q\delta_{q_s}}{\sqrt{B} \sqrt{1 + p^2 + q^2}}.
\]

where \( \delta_{p_s} \neq 0, \delta_{q_s} \neq 0 \), and
\[
A = 1 + p_{s1}^2 + q_{s1}^2,
\]
\[
B = 1 + p_{s2}^2 + q_{s2}^2 + 2p_{s2}\delta_{p_s} + 2q_{s2}\delta_{q_s} + \delta_{p_s}^2 + \delta_{q_s}^2.
\]

The edge of objects can be obtained via zero crossings of the Laplacian \( \nabla^2 R \), where \( \nabla^2 R = R_{xx} + R_{yy} \), and \( R_{xx} \) and \( R_{yy} \) represent second derivatives of \( R \) with respect to \( x \) and \( y \).

In the following sub-sections, analysis of changes between edges and textures of objects for four cases will be given.

2.1. Planar object

In planar lambertian surfaces, the depth, \( z \), does not change. Thus, \( p = z_x = 0, \:\: q = z_y = 0 \) and the image is seen equally bright in all directions. The reflectance map corresponding to planar case is, \( R(p_s, q_s) = 1/\sqrt{1 + p_s^2 + q_s^2} \). The Laplacian of the \( R(p_s, q_s) \) is, \( \nabla^2 R = R_{xx} + R_{yy} = 0 + 0 = 0 \), and the planar case does not have any edges except on the boundaries. Two edge maps obtained for two different illuminations will be the same.

On the other hand, the difference of gray levels between two images of the same planar surface is
\[
|R_1 - R_2| = |\sqrt{B} - \sqrt{A}| / |r \sqrt{B} \sqrt{A}|
\]
and \( \sqrt{B} - \sqrt{A} \neq 0 \). Since \( |z(\nabla^2 R_1) - z(\nabla^2 R_2)| < |R_1 - R_2| \), we can claim that edges are more robust representations than intensity values for planar surfaces.

2.2. Spherical object

For spherical lambertian objects, the depth information is \( z^2 = r^2 - x^2 - y^2 \). Let us assume \( C = r^2 - x^2 - y^2 \). Thus, \( R \) will be
\[
R(p, q; p_s, q_s) = \frac{\sqrt{C} - xp_s - yq_s}{r \sqrt{A}}.
\]

The Laplacian of this reflectance map can be obtained as
\[
\nabla^2 R = (x^2 + y^2 - 2r^2)/r \sqrt{A} \sqrt{C}.
\]

Zero crossings of \( \nabla^2 R \) will occur only when \( x^2 + y^2 = 2r^2 \), which are the boundary locations of the sphere. Hence, the difference between edge maps is \( |z(\nabla^2 R_1) - z(\nabla^2 R_2)| = 0 \). On the other hand, the difference between intensity values is
\[
|R_1 - R_2| = \left| \frac{(\sqrt{C} - xp_s - yq_s)}{r \sqrt{A} \sqrt{B}} \left( \sqrt{B} - \sqrt{A} \right) \right| + \left| \frac{x\delta_{p_s} + y\delta_{q_s}}{r \sqrt{B}} \right|,
\]
which is zero if and only if \( \delta_{p_s} = \delta_{q_s} = 0 \). This reveals that \( |z(\nabla^2 R_1) - z(\nabla^2 R_2)| \leq |R_1 - R_2| \) for the spherical lambertian objects.

We can conclude that edges are more robust features as compared to intensity changes for these specific objects. In the next section, we analyze the effect of illumination change on the edges for the real images.

2.3. Real face images

A human face can be considered as a combination of planar and spherical surfaces discussed above. However, it does not have any analytical expression. In order to observe the importance of non-convex structure on edges, we constructed experiments on real faces of Purdue A & R face database. We used the natural lighting conditions of 113 subject faces as the ideal set and three groups of 339 images as the test set, containing faces illuminated with left, right and both left and right light sources. The three groups and the ideal face and edges associated with them are shown in Fig. 1.

To quantitatively evaluate the effect of variation in illumination for faces, we used the probabilistic measures, \( Pr(IE|DE) \), \( Pr(DE|IE) \) and mean square distance (MSD), where IE is ideal edge and DE is detected edge. The probabilistic calculations for quantitative evaluations are plotted in Fig. 2 for 1 × 1 and 7 × 7 neighborhood masks. As seen from this figure, 7 × 7 neighborhood gives a better performance as compared to 1 × 1. The reason for this is the small displacement of edges due to pose and illumination changes. This reveals that edges cannot be
directly utilized for robust face recognition due to their narrow structure. This problem is solved in our approach by using widened edges obtained by membrane fitting.

3. Eigenhills

Given a set of faces, the classification of faces can be achieved in a low-dimensional descriptive space found by KLT, rather than using a high-dimensional face space. KLT-based approach can be applied for the faces directly [2]. However, this approach suffers from problems related to illumination variation and presence of noise, since it highly depends on local texture of the faces.

Instead of using highly variable local information, more robust descriptive property can be used. Edge maps, which can be obtained by using “generalized edge detector (GED)” [5], are important features that are not distorted by illumination changes as shown in the previous section. However, a drawback of edge-based approach is the locality of edges. Any change in facial expression or a shift in edge locations due to small rotation of the face will degrade the recognition performance. To overcome the locality problem of edges, we introduced spread edge profiles obtained by membrane functional of regularization theory,

\[
E_m(f, \lambda) = \int_\Omega (f - d)^2 \, dx \, dy + \lambda(1 - \tau) \int_\Omega (f_1^2 + f_2^2) \, dx \, dy.
\]

The spread edge profile composes a ghostly face, “hill”. Hills have high values on boundary locations and decrease as we move apart from edges, as shown in Fig. 3. Low-dimensional representation of hills can be determined by KLT by following the algorithm derived in Ref. [2]. Eigenvectors of covariance matrix, defined for hills, is named as “eigenhills”, and they are shown in Fig. 4.

4. Results and conclusion

To show that eigenhills is more robust to illumination changes compared to eigenface and eigenedge approaches, we used real face images by utilizing two criteria: recognition measure, \( \varepsilon = \| W_l - W_t \|_2 \), where \( l \) is learning and \( t \) is test set, and reconstruction error, \( \varepsilon = \| \Gamma_l - \Gamma_t \|_2 \), where \( \Gamma^T \) is reconstructed face.

To observe the performance of real face images, we tested three approaches on 126 individuals of Purdue face database. In experiments, we used natural lighting conditions as learning set, Fig. 5(a), test set of 756 faces consist of six categories: left side light is on, right side source is on, both sidelights are on, and three facial expressions, angry, laughing and screaming, shown in Fig. 5(b).

Average reconstruction error given in Table 1 confirms that eigenhill has better performance compared to eigenedges, and eigenfaces. Eigenedges gave the poorest performance due to non-ideal alignment and low correlation among edge maps.

Recognition performances for the three systems are given in Table 2. From the table it can be observed that the recognition performance for all three lighting conditions for eigenhills is 86.4\%, while it is only 69.8\% for eigenface. Eigenedge method has the poorest recognition performance. Recognition performance of eigenhills for facial expression change is 88.8\%, which is above eigenface’s performance, 88.4\%.
Table 1
Average distance to face space

<table>
<thead>
<tr>
<th></th>
<th>Both sidelight</th>
<th>Left sidelight</th>
<th>Right sidelight</th>
<th>Scream</th>
<th>Laugh</th>
<th>Anger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenface</td>
<td>300</td>
<td>167</td>
<td>219</td>
<td>131</td>
<td>80</td>
<td>98</td>
</tr>
<tr>
<td>Eigenedge</td>
<td>250</td>
<td>252</td>
<td>250</td>
<td>258</td>
<td>236</td>
<td>252</td>
</tr>
<tr>
<td>Eigenhill</td>
<td>151</td>
<td>108</td>
<td>120</td>
<td>140</td>
<td>86</td>
<td>109</td>
</tr>
</tbody>
</table>

Table 2
Recognition performances

<table>
<thead>
<tr>
<th></th>
<th>Both sidelight</th>
<th>Left sidelight</th>
<th>Right sidelight</th>
<th>Scream</th>
<th>Laugh</th>
<th>Anger</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenface</td>
<td>44.7</td>
<td>85.8</td>
<td>79.1</td>
<td>83.8</td>
<td>93</td>
<td>89</td>
</tr>
<tr>
<td>Eigenedge</td>
<td>18.7</td>
<td>34.2</td>
<td>27.5</td>
<td>16.7</td>
<td>42</td>
<td>30</td>
</tr>
<tr>
<td>Eigenhill</td>
<td>80.2</td>
<td>91.6</td>
<td>87.5</td>
<td>79.8</td>
<td>95</td>
<td>92</td>
</tr>
</tbody>
</table>

Note that, overall recognition performance of eigenhill is 89.4%, which is above eigenface’s overall recognition performance, 82.3%. Also, overall performance of the eigenedge method, 38.8%, is below the acceptable range.

From the results of the experiments given above, we conclude that eigenhills approach is more robust to illumination variation than eigenface and eigenedge for face recognition.

References


