Hybrid image matching combining Hausdorff distance with normalized gradient matching

Chyuan-Huei Thomas Yang\textsuperscript{a}, Shang-Hong Lai\textsuperscript{b,\#}, Long-Wen Chang\textsuperscript{b}

\textsuperscript{a}Department of Computer Science, Hsuan Chuang University, Taiwan, ROC
\textsuperscript{b}Department of Computer Science, National Tsing Hua University, Hsinchu City 300, Taiwan 300, ROC

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Abstract

Image matching has been a central problem in computer vision and image processing for decades. Most of the previous approaches to image matching can be categorized into the intensity-based and edge-based comparison. Hausdorff distance has been widely used for comparing point sets or edge maps since it does not require point correspondences. In this paper, we propose a new image similarity measure combining the Hausdorff distance with a normalized gradient consistency score for image matching. The normalized gradient consistency score is designed to compare the normalized image gradient fields between two images to alleviate the illumination variation problem in image matching. By combining the edge-based and intensity-based information for image matching, we are able to achieve robust image matching under different lighting conditions. We show the superior robustness property of the proposed image matching technique through experiments on face recognition under different lighting conditions.

Keywords: Image matching; Illumination variation; Face recognition; Hausdorff distance; Normalized gradient

1. Introduction

Image matching is one of the most fundamental problems in computer vision, image processing and pattern recognition. It is often required in object recognition, pattern search, industrial inspection and image sequence analysis. For object recognition from images, we need to compare the input image with the training images in the database to determine which training image is most similar to the input image. Pattern search is to locate similar image pattern from the input image. For industrial inspection, the main goal is to detect defect regions from the inspection image by comparing it with the reference image. Image sequence analysis normally requires track targets across frames, which can be done by matching target image regions in the next image frame. Image matching is normally based on maximizing an image similarity measure for two given images. For example, normalized correlation is an image similarity measure commonly used in various problems.

A robust image similarity measure is imperative for matching images under very different conditions that lead to very different image appearances. For example, face recognition under very different lighting conditions is a very challenging problem. It requires a robust image matching algorithm to select an image from the face image database that best matches the input face image under different lighting conditions. The geometrics-based image matching approach has been regarded to be more robust against the intensity-based image matching approach. For the former, Hausdorff distance and its variants have been recognized to provide an effective way for image matching mainly because feature correspondence is not required.

There have been a number of previous methods proposed based on Hausdorff distance function for image matching [1–5]. Gualtieri et al. [1] presented two efficient algorithms for matching images based on the classical
Hausdorff distance. You et al. [2] applied the Hausdorff distance based matching scheme to the interesting points instead of edge maps for comparing images. Gesu and Starovoitov [3] defined several image distance functions, included Hausdorff-based, local distance based, global feature based, and symmetry based to compare images in the JACOB pictorial database. Ghafoor et al. [4] proposed an extension of the distance transform (chamfer) matching to be a robust image matching algorithm. Perlibakas [5] compared 14 distance measures, such as \( L_p \), mean square error (MSE), ..., etc., with the principle component analysis (PCA)-based face recognition, and proposed a modified sum of square errors (SSE)-based distance function for face recognition.

Several researchers proposed modifications of Hausdorff distance to develop object similarity measures for different purposes [6–11]. One of the most distinguished benefits of Hausdorff distance is that it does not require point correspondences between two objects or two images. Huttenlocher et al. [6] applied the directed Hausdorff distance and developed efficient algorithms for image alignment with this distance. Dubuisson and Jain [7] developed several modified Hausdorff distances (MHD) for comparing the edge maps computed from the gray-scale images. Paumard [8] proposed a censored Hausdorff distance (CHD) for comparing binary images. Takacs [9] introduced the neighborhood function and associated penalties to extend the MHD for face recognition. In addition, Sim et al. [11] combined the Hausdorff distance with the M-estimation and least trimmed square estimation to achieve robust image matching.

The geometrics-based image matching approach is recognized to be more robust against non-even lighting variations than the intensity-based approach. A number of previous works have been developed to apply Hausdorff distance for object recognition [12–17]. Yi and Camps [12] presented a line-based recognition algorithm by using a four-dimensional Hausdorff distance in conjunction with the line-feature comparison for model-based recognition. Gao and Leung [13] incorporated the structural and spatial information by using the dominant points of a human face edge map to extract a set of line segments for face representation, then they applied Hausdorff distance to compute the similarity measure between face images. The resulting matching score is called the line segment Hausdorff distance (LHD). Guo et al. [14] proposed a new modified Hausdorff distance which is weighted by a function derived from the spatial information of human face. Furthermore, Lin et al. [15] proposed modified Hausdorff distances with spatial weighting determined by eigenface features. The eigenface-based weighting function provides more weighting on important facial features, such as eyes, mouth, and face contour. Zhu et al. [16] employed an improved Gabor filter for computing edge maps and applied a weighted modified Hausdorff distance (WMHD) in a circular Gabor feature space for comparing images. Kwon et al. [17] proposed a robust hierarchical Hausdorff distance to compare edge maps in a multi-level pyramid structure.

Face recognition under different illumination variations has been recognized to be an important and challenging problem [18–21] in face recognition. Although the aforementioned geometrics-based methods are more robust against smooth brightness variations, this approach relies on reliable extraction of edge or geometrical features from face images captured under different conditions. A considerable amount of efforts have been endeavored on the intensity-based image matching camp. Georgiades et al. [18] proposed a novel algorithm for comparing face images under different illumination conditions by introducing an illumination cone, which is constructed from several images of the same person captured at the same pose under different illumination directions. In addition, Zhao and Chellappa [19] developed a 3D shape-based face recognition algorithm by using an illumination-independent ratio image, which is derived from symmetric shape-from-shading analysis on face images. Yang et al. [20] presented an illumination insensitive face matching algorithm by using a robust image similarity measure based on comparing the corresponding normalized image gradient fields to achieve a robust face matching. Shan et al. [21] proposed to combine several different pre-processing steps to achieve robust face recognition against different lighting changes. Their pre-processing procedure consists of a gamma intensity correction method, the histogram equalization technique to eliminate the sidelighting effect, and a new quotient illumination relighting method to alleviate the brightness variations due to lighting changes.

In this paper, we propose a hybrid image matching algorithm by integrating the geometrics-based and intensity-based cues for robust image matching. To be more specific, the proposed image similarity measure combines a modified Hausdorff distance with the normalized image gradient matching [20]. We apply the integrated image similarity measure to the problem of face recognition under different illumination conditions. Experimental results on some well-known face datasets show the proposed algorithm outperforms some previous methods for face recognition under different illumination variations.

The rest of this paper is organized as follows. We describe the Hausdorff distance and the modified Hausdorff distances in the next section. In Section 3, the proposed hybrid image matching algorithm that integrates the modified Hausdorff distance with the normalized image gradient matching is described. We show some experimental results by using the proposed algorithm and some previous methods on Yale face database B and CMU face database to demonstrate its superior performance on face recognition under different lighting conditions. Finally, conclusions are given in the last section.

## 2. Hausdorff distance

The original Hausdorff distance was proposed for comparing two binary images by Huttenlocher et al. [6]. The
computation of Hausdorff distance does not require point correspondences between the two point sets. They proposed efficient computational algorithms for speeding up the process of finding similar patterns in an image by searching the regions with the smallest Hausdorff distances in the image [6]. Since the original Hausdorff distance method is not sensitive to small perturbations in point locations for shape alignment, so there have been several modified versions of Hausdorff distance proposed later. In this section, we reviewed the original Hausdorff distance and some of its modified versions.

2.1. The Hausdorff distance

The Hausdorff distance [3], adopted for the comparison of two images, is to calculate the maximal inter-pixel distance between their corresponding edge point sets. For two sets of points \( X = \{ x_1, x_2, x_3, \ldots, x_{N_X} \} \) and \( Y = \{ y_1, y_2, y_3, \ldots, y_{N_Y} \} \), with each vector \( x_i \) or \( y_j \) representing a 2D image coordinate of edge point extracted from the image. We can define the Hausdorff distance for the two point sets \( X \) and \( Y \) as follows:

\[
HD(X, Y) = \max_{i,j} \{ d(x_i, Y), d(y_j, X) \},
\]

(1)

where \( d \) is a metric defined in 2D image space to compute the distance from a pixel \( x_i \) to the point set \( Y \). It is given by

\[
d(x_i, Y) = \min_{y_j \in Y} \{ d(x_i, y_j) \}.  
\]

(2)

Similarly, it is used to compute the distance from a pixel \( y_j \) to the point set \( X \), that is,

\[
d(y_j, X) = \min_{x_i \in X} \{ d(y_j, x_i) \}. 
\]

(3)

The city-block, chessboard, or Euclidean distance can be employed for the distance function \( d \) between two 2D points \( x = (x_1, x_2) \) and \( y = (y_1, y_2) \), i.e.,

\[
d_{\text{chess}}(x, y) = \max(|x_1 - y_1|, |x_2 - y_2|), \quad d_{\text{city}}(x, y) = |x_1 - y_1| + |x_2 - y_2|, \quad d_{\text{E}}(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}. 
\]

(4) \hspace{1cm} (5) \hspace{1cm} (6)

Note that the city-block or chessboard distance is often used to replace the Euclidean distance from the consideration of faster computational speed.

2.2. Modified Hausdorff distance

Dubuisson and Jain [7] developed several modified Hausdorff distances (MHD) for comparing two point sets extracted from the corresponding gray-scale images. The directed distance of a point set \( X \) to another point set \( Y \) can be defined in the following different ways:

\[
d_1(X, Y) = \min_{x \in X} d(x, Y), \quad d_2(X, Y) = \max_{x \in X} d(x, Y), 
\]

(7) \hspace{1cm} (8)

\[
d_3(X, Y) = \frac{1}{N_X} \sum_{x \in X} d(x, Y), 
\]

(9)

\[
d_4(X, Y) = a K_{x \in X} d(x, Y), 
\]

(10)

where \( a K_{x \in X} \) represents the \( K^{th} \) ranked distance such that \( K/|X| = a\% \) and \( |X| \) is the cardinal number of the set \( X \). Therefore, \( 50 K_{x \in X} \) means the median of the distance \( d(x, Y) \), for all \( x \in X \). Note that the above distances are all directed. Some of the undirected Hausdorff distance measures can be defined as follows:

\[
D_1(X, Y) = \min(d(X, Y), d(Y, X)), 
\]

(11)

\[
D_2(X, Y) = \max(d(X, Y), d(Y, X)), 
\]

(12)

\[
D_3(X, Y) = \frac{d(X, Y) + d(Y, X)}{2}, 
\]

(13)

\[
D_4(X, Y) = \frac{|X|d(X, Y) + |Y|d(Y, X)}{|X| + |Y|}. 
\]

(14)

The function with the combination \( D_2-d_2 \) is the standard Hausdorff distance. The other combinations are not metrics, since they do not satisfy the triangle inequality. The combination of \( D_2 \) with \( d_4 \) is called the best partial distance given by

\[
HD_a(X, Y) = \max (a K_{x \in X} d(x, Y), a K_{y \in Y} d(y, X)). 
\]

(15)

We will use the combinations of \( D_2 \) with \( d_2-d_4 \) as the distance functions in our hybrid image matching method.

3. Proposed hybrid image similarity measure

The Hausdorff distance and its variants described above have been employed for measuring the distance between two point data sets, such as shape comparison. These distances are purely geometrics-based. Recently, Gesù and Starovoitov [3] proposed a new image similarity measure that combines the Hausdorff distance and grayscale difference to achieve more reliable image matching. They presented different combined similarity measures between two pixels in two different images based on the city-block, chessboard, and Euclidean distances, as given below:

\[
d_{\text{city}}(x, y; I, F) = \omega_1 |x_1 - y_1| + |x_2 - y_2| + \omega_2 |I(x) - F(y)|, 
\]

(16)

\[
d_{\text{chess}}(x, y; I, F) = \max \{ \omega_1 |x_1 - y_1|, \omega_1 |x_2 - y_2|, \omega_2 |I(x) - F(y)| \}, 
\]

(17)
where \( x \) and \( y \) are location vectors of two pixels in the two images \( I \) and \( F \), respectively, \( \omega_1 \) and \( \omega_2 \) are the weights associated with the geometric location distance and the intensity difference, respectively. This combined similarity measure integrates the geometrical distance and intensity differences for more reliable image matching. However, the above integrated similarity measure cannot account for large differences for more reliable image matching. However, the above integrated similarity measure cannot account for large gray-scale deviations due to illumination variations. To alleviate the illumination variation problem for the intensity-based image matching approach, Yang et al. [20] proposed to match the normalized gradient fields instead. The image similarity measure is defined as the consistency between the corresponding normalized gradient vectors with appropriate intensity weighting to reduce the influence of very bright and dark regions to the image matching. This similarity measure is given by [20]

\[
E(x, y; I, F) = \sum_{(m,n) \in W_x} |\nabla I(m, n)| + c \cdot \sum_{(m,n) \in W_y} |\nabla F(m, n)| + c,
\]

(19)

where \( \nabla I(x) \) and \( \nabla F(y) \) are the gradient vectors of the two images \( I \) and \( F \) at the corresponding locations \( x \) and \( y \), respectively. The denominators in the above equation are the local maximums of absolute gradients in a local window \( W \) centered at the corresponding location and \( c \) is a small positive constant used to prevent dividing by zero or a very small number. The symbol “\( \cdot \)” denotes the inner product. By combining the Hausdorff distance with the normalized gradient consistency measure, we have modified the city-block, chessboard, and Euclidean distances as follows:

\[
d'_{\text{city}}(x, y; I, F) = \omega_1(|x_1 - y_1| + |x_2 - y_2|) + \omega_2|1 - E(x, y; I, F)|,
\]

(20)

\[
d'_{\text{chess}}(x, y; I, F) = \max(\omega_1|x_1 - y_1|, \omega_1|x_2 - y_2|, \omega_2|1 - E(x, y; I, F)|),
\]

(21)

\[
d'_{\text{Euclidean}}(x, y; I, F) = \sqrt{\omega_1((x_1 - y_1)^2 + (x_2 - y_2)^2) + \omega_2(1 - E(x, y; I, F))^2}.
\]

(22)

We apply these 3D metrics with the modified Hausdorff distance for matching two gray-scale images with their corresponding edge maps. Thus we have the MHD with the normalized gradients and the city-block, chessboard, or Euclidean distance measures, as given in Eqs. (20)–(22), respectively. Thus, the similarity measure of the MHD with the normalized gradient matching is defined as follows:

\[
S_{MHD}(X, Y; I, F) = \max \left\{ \frac{1}{|X|} \sum_{x \in X} d_{Y,F}(x; I), \frac{1}{|Y|} \sum_{y \in Y} d_{X,I}(y; F) \right\},
\]

(23)

where \( X \) and \( Y \) are the sets of 2D coordinates of the edge points for the template and search images \( I \) and \( F \), respectively. Note that \( |X| \) and \( |Y| \) are the total numbers of pixels in the sets \( X \) and \( Y \), respectively. In addition, the distance \( d_{Y,F}(x; I) \) or \( d_{X,I}(y; F) \) is defined in the same way as follows:

\[
d_{Y,F}(x; I) = \min_{y \in Y} [d'(x, y; I, F)],
\]

(24)

\[
d_{X,I}(y; F) = \min_{x \in X} [d'(x, y; I, F)],
\]

(25)

where the function \( d' \) can be the city-block, chessboard, or Euclidean distance as given in Eqs. (20)–(22), respectively. If we use the ranked distance with the modified Hausdorff distance, then we have following similarity measure for image matching.

\[
S_{RMHD}(X, Y; I, F) = \max_{a, b} \left( a K_{x \in X} d_{Y,F}(x; I), a K_{y \in Y} d_{X,I}(y; F) \right).
\]

(26)
To illustrate the information we used for image matching in the proposed hybrid image similarity measure, we show the edge map and the normalized gradient field computed from a face image in Fig. 1. In the next section, we will show some experimental results of using the proposed image matching algorithm on face recognition problem to demonstrate its robustness of face image matching under different illumination conditions.

4. Experimental results

To evaluate the performance of the proposed image matching algorithm combining the Hausdorff distance with the normalized gradient consistency measure, we apply it to the problem of face recognition under illumination variations. We tested the proposed image matching algorithm on the Yale Face Database B [18], which was built by Center for Computational Vision and Control at Yale University. We also compare the performance of face recognition on this dataset for the proposed image matching algorithm with other previous methods.

The Yale Face Database B contains 10 subjects (persons). The dataset for each subject contains nine poses and 64 different illumination conditions that yield 576 viewing conditions for each subject. In this paper, we focus on the face recognition problem under different illumination conditions but with the same face pose. Due to this reason, we used not all of the total face images in the database in our experiment. Instead, we select all the face images at pose 0, i.e. the frontal pose, under different illumination conditions in our experiment. We choose the images with the filename extensions ‘P00A + 000E + 00’ as our reference images. Fig. 2 shows these reference template images of all subjects in our experiment. For the condition [20] that requires three reference images, two additional face images indexed ‘P00A – 050E + 00’ and ‘P00A + 050E + 00’, corresponding to the left (50 degree) and right (50 degree) light direction, are used as the reference images. In our experiment, we chose 36 frontal face images with different illumination conditions from those of the reference images in the Yale Face Database B to be our test images. Therefore, there are totally 360 images in our test image set. Fig. 3 shows the 36 test images for one subject under different illumination conditions.

In our implementation of applying the proposed hybrid image similarity measure for face recognition, we first applied a simple smoothing operator on the face image before computing the image gradient for reducing noise and spreading out the support of gradient function around edge locations. Note that both of the parameters \( \omega_1 \) and \( \omega_2 \) are set to 1 in our experiments, but in general they can be adjusted appropriately to achieve the best result. We compare the proposed algorithm with previous Hausdorff-distance based image matching methods and some previous face recognition methods on the Yale face database B dataset. Fig. 4 depicts an example of face recognition by using the proposed algorithm. The recognition results on the test image set are summarized in Tables 1 and 2. Table 1 shows the proposed image matching algorithm, which combines the geometrical distance with the normalized gradient matching, significantly outperforms the previous methods [3] that incorporate the gray-scale matching into the Hausdorff-distance. We also compare the proposed hybrid image matching algorithm, in conjunction with the metric \( d'_E \), with the isotropic derivatives method, 2D Gabor-filter method, and the Fisher-face method and the normalized gradient matching method [20] on the same face dataset. The recognition results summarized in Table 2 demonstrate the superior performance of the proposed algorithm over the other methods.

We also implemented the partially ranked Hausdorff distances with 50\(^{th}\) ranked, 75\(^{th}\) ranked, and 90\(^{th}\) ranked in conjunction with the proposed hybrid similarity measure, but the recognition rates are slightly less than the modified Hausdorff distance in our experiment on this dataset. Figs. 5–8 depicts a case in our experiment that the previous Hausdorff-base distance integrated with gray-scale matching failed to recognize the face image correctly under different illumination conditions, but the proposed image matching algorithm based on a hybrid image similarity measure can do the job correctly.

In the following, we show some experimental results of applying the proposed robust image matching algorithm to face images acquired with not only illumination variations but also pose and scale variations. We first used the face images with different pose and illumination conditions in Yale
The face images indexed by yaleB01_P01A+000E+00, yaleB01_P02A+000E+00, yaleB01_P03A+000E+00, ..., and yaleB01_P08A+000E+00 are shown in Fig. 9 and depict the eight different pose variations included in this experiment. There are 10 subjects with eight different poses and 36 different illumination conditions in the testing image dataset. The reference images used in the experiments are all frontal face images. The experimental results of using normalized gradient matching method (NG) [20], the modified Hausdorff distance matching method (HD), and the proposed hybrid matching algorithm are summarized in Table 3. The accuracy is decreased as the pose variation is large since we used only the frontal face image as the reference image in the experiments. However, we can still see the proposed hybrid algorithm provides the best result.

Finally, we also examine the performance of the proposed hybrid matching algorithm with different image scaling and illumination variations. We simulate the scaling effect on the same 36 frontal face images for each person under different illumination conditions from Yale B face database with the scaling factors 0.8, 0.9, 1.0, 1.1, and 1.2. These testing images cover scaling variations within ±20%. This face
Fig. 5. (a) A face template image indexed yaleB10_P00A + 00E + 00; (b) its edge map; (c) its normalized gradient field; and (d) the face with the normalized gradient field overlaid.

Fig. 6. (a) A test image indexed yaleB10_P00A + 060E + 20 in Yale B face database; (b) the recognition result by using the MHD with the edge map of the recognized subject in 5(b) overlaid to the face image; (c) the normalized gradient field computed from the face region in (a); (d) the recognition result by using the proposed hybrid image matching algorithm with the normalized gradient field of the recognized subject in 5(c) overlaid to the face image.

Fig. 7. (a) A face template image indexed yaleB08_P00A + 000E + 00; (b) its edge map; (c) its normalized gradient field; and (d) the face image with the normalized gradient field overlaid.

Fig. 8. (a) A test image indexed yaleB08_P00A + 020E − 40 in Yale B face database; (b) the recognition result by using the MHD with the edge map of the incorrectly recognized subject in 5(b) overlaid to the face image; (c) the normalized gradient field computed from the face region in (a); (d) the recognition result by using the proposed hybrid image matching algorithm with the normalized gradient field of the correctly recognized subject in 7(c) overlaid to the face image.

Recognition experiment contains 10 persons with 180 face images for each person under different illumination conditions and scaling factors as the testing image dataset. The accuracy of face recognition by using the NG, HD, and the proposed hybrid matching algorithm to these testing images are summarized in Table 4. The experimental results show the proposed hybrid matching algorithm outperforms the previous methods.
Table 3
Experimental results of face image recognition under pose and illumination variations by using the normalized gradient (NG), Hausdorff distance (HD) and the proposed hybrid methods on the Yale B face database

<table>
<thead>
<tr>
<th></th>
<th>NG(%)</th>
<th>HD(%)</th>
<th>Hybrid(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>73.61</td>
<td>49.17</td>
<td>76.11</td>
</tr>
<tr>
<td>P02</td>
<td>67.22</td>
<td>42.22</td>
<td>68.61</td>
</tr>
<tr>
<td>P03</td>
<td>58.33</td>
<td>48.06</td>
<td>62.22</td>
</tr>
<tr>
<td>P04</td>
<td>57.78</td>
<td>43.89</td>
<td>63.61</td>
</tr>
<tr>
<td>P05</td>
<td>49.72</td>
<td>42.22</td>
<td>56.67</td>
</tr>
<tr>
<td>P06</td>
<td>47.78</td>
<td>34.44</td>
<td>51.39</td>
</tr>
<tr>
<td>P07</td>
<td>48.89</td>
<td>31.94</td>
<td>48.89</td>
</tr>
<tr>
<td>P08</td>
<td>41.39</td>
<td>34.72</td>
<td>48.61</td>
</tr>
<tr>
<td>Average</td>
<td>55.59</td>
<td>40.83</td>
<td>59.51</td>
</tr>
</tbody>
</table>

Table 4
Experimental results of face recognition under zooming and illumination variations by using the normalized gradients (NG), Hausdorff distance (HD) and the proposed hybrid methods

<table>
<thead>
<tr>
<th>Scaling factor</th>
<th>NG(%)</th>
<th>HD(%)</th>
<th>Hybrid(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.8</td>
<td>92.50</td>
<td>81.94</td>
<td>93.33</td>
</tr>
<tr>
<td>0.9</td>
<td>93.61</td>
<td>83.33</td>
<td>95.00</td>
</tr>
<tr>
<td>1.0</td>
<td>94.72</td>
<td>84.72</td>
<td>97.50</td>
</tr>
<tr>
<td>1.1</td>
<td>93.33</td>
<td>83.61</td>
<td>95.28</td>
</tr>
<tr>
<td>1.2</td>
<td>92.78</td>
<td>82.50</td>
<td>93.61</td>
</tr>
<tr>
<td>Average</td>
<td>93.39</td>
<td>83.22</td>
<td>94.89</td>
</tr>
</tbody>
</table>

5. Conclusions

We proposed a novel hybrid face matching algorithm that integrates the Hausdorff distance with normalized gradient matching. It not only considers real locations of the corresponding edge pixels but also includes the consistency of the normalized gradient in the image matching. Thus this hybrid image matching algorithm combines both the geometric information and the reliable intensity gradient information to achieve robust image matching. It does not require point correspondences between two objects or two images during the image matching process. Experimental results of applying the proposed hybrid image matching algorithm to the problem of face recognition under different illumination conditions show its superior recognition rate over several previous face recognition methods.

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References


About the Author—CHYANG-HUEI THOMAS YANG received the B.S. degree in mathematics from Tamkang University, Taipei County, Taiwan in 1986, the M.S. degree in computer science from New Jersey Institute Technology, Newark, New Jersey, USA in 1992, and the Ph.D. degree in computer science from National Tsing-Hua University, Hsinchu City, Taiwan in 2005. Now he is an assistant professor in the Department of Computer Science, Hsuan-Chuang University, Hsinchu City, Taiwan. His research interests include image processing, computer vision, pattern recognition, face recognition, information hiding, steganography, and watermarking.

About the Author—SHANG-HONG LAI received the B.S. and M.S. degrees in electrical engineering from National Tsing Hua University, Hsinchu, Taiwan, and the Ph.D. degree in electrical and computer engineering from University of Florida, Gainesville, in 1986, 1988 and 1995, respectively. He joined Siemens Corporate Research in Princeton, New Jersey, as a member of technical staff in 1995. Since 1999, he returned to Taiwan as a faculty member in the Department of Computer Science, National Tsing Hua University. He is currently an associate professor in the same department. In 2004, he was a visiting scholar with the Department of Electrical Engineering, Princeton University. Dr. Lai’s research interests include computer vision, visual computing, pattern recognition, medical imaging, and multimedia signal processing. He has authored more than 90 papers published in the related international journals and conferences. Dr. Lai holds 10 US patents for inventions related to computer vision and medical image analysis. He has been a member of program committee of several international conferences, including CVPR, ICCV, ECCV, ACCV, ICPR and ICME.

About the Author—LONG-WEN CHANG received B.S. of Electrical Engineering from National Cheng Kung University in 1976 and M.S. and Ph.D. of Electrical Engineering and Computer Engineering from University of New Mexico in 1980 and 1984, respectively. In 1984, he joined the Institute of Computer Science of National Tsing Hua University Taiwan. His interests include image processing, computer vision, computer graphics and information security and data hiding and digital watermarking. Dr. Chang is a professor of the Department of Computer Science and Institute of Information Systems and Applications in National Tsing Hua University, Hsinchu, Taiwan. Dr. Chang was invited to serve as a technical committee member including SPIE Conference on VCIP, IEEE ICME, a program committee member for STEG. He received an Excellent Research Award from National Science Council.